NBER WORKING PAPER SERIES

HOW CURVY IS THE PHILLIPS CURVE?

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Working Paper 33234
http://www.nber.org/papers/w33234

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
December 2024

The authors would like to thank Jose Barrero, Steve Davis, Kevin Foster, Brent Meyer, and Emil Mihaylov for the US data, and the Economic and Social Research Council for funding under grant ES/X013707/1. The authors also benefitted from comments by seminar participants in Princeton, Chicago Fed, Boston College, Bristol, LSE, UCL, Warwick, Nottingham, Sciences Po, Banca d'Italia, the IMF as well as at the BCEA, ICEA, ECB, ASSA, SITE, CBBS, MMF, RES, and SUERF conferences. Any views expressed are solely those of the authors and so cannot be taken to represent those of the Bank of England or to state Bank of England policy. This paper should therefore not be reported as representing the views of the Bank of England or members of the Monetary Policy Committee, Financial Policy Committee, or Prudential Regulation Committee. The views expressed herein are those of the authors and do not necessarily reflect the views of the National Bureau of Economic Research.

At least one co-author has disclosed additional relationships of potential relevance for this research. Further information is available online at http://www.nber.org/papers/w33234

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How Curvy is the Phillips Curve?
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NBER Working Paper No. 33234
December 2024
JEL No. C83, D22, D84, E31

ABSTRACT

Macro data suggests a convex relationship between inflation and economic slack, but identifying causality is challenging. Using micro data from large panel surveys of UK and US firms we show that the response of prices to demand shocks is also convex at the firm level. We obtain similar results using three different empirical exercises examining: the impact of COVID demand shocks, the response to sales shocks, and hypothetical shocks from a survey question. This convexity is strongest in firms and industries with higher inflation, disappears in horizons beyond two years, and is also present in response to cost shocks. We rationalize these findings in a menu cost model with positive trend inflation and decreasing returns at the firm level, which replicates firm and aggregate Phillips curve convexity. The non-linearity emerges from trend inflation pushing firms closer to their price increase thresholds.

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1 Introduction

In 2022, inflation across many advanced economies reached levels not seen for decades (Figure 1). The extent of this increase in inflation was greater than most forecasters had expected, even given the rises in energy prices after the Russian invasion of Ukraine and shortages of labor and intermediate goods. Since then, inflation rates have fallen, and by the fourth quarter of 2024 were again close to target levels. Understanding the dynamics of this inflation episode is crucial for monetary policymakers setting interest rates in response to large shocks. But analyzing the current period is also important from a more timeless perspective – providing identifying variation to improve our understanding of firm price-setting, and specifically to identify potential non-linearities in the response to shocks.[1]

The canonical approach to modelling aggregate inflation dynamics is the Phillips curve, which considers the relationship between measures of inflation and economic slack.[2] Cross-country macro data provide suggestive evidence of a convex relationship, but achieving proper identification with aggregate data is econometrically challenging. In this paper, we use data from large and representative surveys of UK and US firms to causally identify how prices respond to firm-level demand shocks, and, separately, cost shocks.[3] In the second part of the paper, we develop a general equilibrium model with menu costs to rationalize the micro-level estimates and analyze the implications for the aggregate Phillips curve.

We use data from the Decision Maker Panel (DMP) survey for the UK, and auxiliary data from the Survey of Business Uncertainty (SBU) in the US.[4] The UK DMP is a large and representative survey of CFOs in UK businesses.[5] It was established in 2016 and is run by the Bank of England in partnership with the University of Nottingham and King's College London. The survey is carried out online and receives close to 2,500 responses each month. In the survey, firms are asked how the average price that they charge has changed over the last year. Firms are also asked how they expect their own prices to change over the next year. This question asks about the distribution of expectations, allowing both a point estimate and a

[1] Other papers have also considered non-linearities in the current context, including Ball et al. (2022), Benigno and Eggertsson (2023, 2024), Boehm and Pandalai-Nayar (2022), Harding et al. (2023), and IMF (2024), among others.

[2] The specific measures of inflation and economic slack used vary substantially in the literature. In the original 1958 paper, Phillips used monthly wage growth and unemployment, respectively.

[3] Existing papers have used regional data from the US to identify the slope of the Phillips curve. See, for example, Beraja et al. (2019), McLeay and Tenreyro (2019), Fitzgerald et al. (2020), and Hazell et al. (2022).

[4] Aggregate statistics from the surveys are published on a monthly basis on the DMP and SBU websites https://decisionmakerpanel.co.uk/ and https://www.atlantafed.org/research/surveys/business-uncertainty

[5] Further information on the structure of the DMP, evaluation of data quality, and how the data can be accessed are detailed in Bunn et al. (2024).

measure of uncertainty around expected own-price inflation to be calculated.[6] The US SBU is organized in a similar manner, run by the Federal Reserve Bank of Atlanta collecting monthly data from up to 1,000 firms.[7]

We find significant evidence that the response of firm prices to demand shocks is convex; firms increase their own-price growth by a larger amount in response to positive shocks than they reduce them in response to negative shocks. This convexity is revealed using three distinct approaches, utilizing different survey questions.

First, we run a survey experiment that asks firms how they would adjust their prices in response to a series of hypothetical sales volume shocks, ranging from −20% to +20%. The size, sign, and the order in which we ask the response are randomly chosen, and each firm is then asked the same question with the shock sign reversed. We find strong evidence of convexity, with firms raising prices in response to positive shocks, whereas the response to negative shocks is around zero.

Second, using responses from firms about their own price-setting behavior, we focus on information about expected future price changes. Rather than using this information in its raw form, which might distort our results if some firms have larger expected price changes than others, we calculate firm-level price growth forecast errors. This is the difference between realized annual price growth and expected year-ahead price growth reported a year earlier. We do the same using expected and actual sales growth and then analyze the relationship between sales growth and price growth forecast errors, which are both scale free. The results again suggest a significant asymmetry, with positive sales growth forecast errors associated with more than two times larger price growth forecast errors. Importantly, we show that this relationship is present in the years before the pandemic and in the period since 2020.

Finally, we analyze the response of firm prices to the Covid-19 shock. The impact of Covid-19 is estimated using specific questions about the impact of the pandemic on firm sales. Once again, we find that the effect on inflation was asymmetric: positive demand shocks from Covid raised inflation at the firm level by five times more than negative Covid demand shocks reduced it. This demand asymmetry helps to explain why inflation did not fall by more during the pandemic but accelerated during the rebound.

[6] A previous version of this working paper (Bunn et al. 2022) included a section on firm-level inflation *uncertainty*. This inflation uncertainty material has now been published in Yotzov et al. (2023).
[7] See, for example, Altig et al. (2022)

We then present three extensions to our main results, which provide additional predictions for our model to verify. Many models predict a convex Phillips curve – for example models with menu costs, capacity constraints, financial constraints, non-linear demand curves, or wage rigidities. So, we provide three extensions to distinguish between these different models.

First, we show that the convexity of the price response to demand shocks is more pronounced when inflation is high. We split the sample into high-inflation and low-inflation firms using firm average price growth across all survey months relative to the 4% full sample average. Firms with average price growth above 4% (mean of 7%) exhibit a strongly non-linear response to positive versus negative shocks across all three empirical exercises described above. In contrast, firms with average price growth below 4% (mean of 1.5%) do not exhibit material convexity in their price response to demand shocks.

Second, we show that our convex response is only present in shorter-run responses. The main analysis uses survey questions asking about year-on-year price and sales changes. In the second exercise, we utilize the panel dimension of the survey to analyze longer-run responses by looking at *cumulative* price growth and sales growth changes over several years. We find evidence that the convexity of price response to sales is strongest in the first year, and declines over time, so by the fourth year the convexity has disappeared.

Third, we analyze the response of firm prices to *cost* shocks, which we show are also strongly convex. First, we run a randomized survey experiment where firms are asked about price responses to hypothetical *unit cost* shocks. The results using our randomized assignment of shock size, sign, and order, suggest a convexity in prices responses. Firms report a 60% cost pass-through to positive shocks in the first year after a shock, but only a 20% pass-through to negative shocks. We also consider the relationship between unit cost growth forecast errors and price growth forecast errors. We find that the response to positive errors is more than twice as strong as that to negative errors. The non-linear response to cost shocks is consistent with the large increase in price growth over 2022, which was driven, to a large extent, by higher firm costs.[8]

These empirical results are rationalized in a model of firm price setting with menu costs, decreasing returns to scale, and positive trend inflation. Decreasing returns to scale increase

[8] In a previous working paper version of this paper (Bunn et al. 2022), we use a regression-based decomposition to assess the main drivers of price growth up to 2022Q2. The largest contributions were from energy costs, supply disruptions, and recruitment difficulties.

firms' optimal prices when output increases relative to the aggregate. But menu costs create an (S,s) inaction region for firms in which prices do not change in response to cost or demand shocks. Positive trend inflation generates an asymmetry in the distribution of firms within the inaction zone, as positive inflation leaves more firms closer to the price-increase point (the upper S bound) than firms close to their price reduction point (the lower s bound). So, price increases are more likely to be triggered by positive demand shocks than reductions triggered by negative demand shocks of a similar size.

Simulated data from the model delivers a convex relationship between firm-level demand shocks and firm price inflation, matching our empirical results. Aggregating these responses, we find that the *aggregate* Phillips curve is also convex. Importantly, this model can also explain our three empirical extensions: convexity is greater with higher tend inflation, convexity wanes over the longer-run, and the price response to cost shocks is also convex.

Related Literature Our work relates to four different strands of literature: (i) the asymmetric response of inflation to shocks; (ii) how firms set prices and the reasons behind their pricing decisions; (iii) micro data on price non-linearities and (iv) using firm surveys to evaluate the impact of major shocks.

The rise in inflation across the world in 2021-2022 prompted a renewed interest in studying price-setting behavior and the potential for non-linearities. Several recent papers are particularly relevant to the present study. Benigno and Eggertsson (2023, 2024) find evidence that the aggregate wage Phillips curve is non-linear in labor market tightness and posit a model with a frictional labor market with downwardly rigid wages and a discontinuity in wage setting behavior when labor market tightness exceeds a certain value. Harding et al. (2023) posit a quasi-kinked demand schedule for goods which generates a non-linear aggregate Phillips curve and use this to explain both the missing deflation during the Great Recession and the acceleration in aggregate inflation during 2022. In Boehm and Pandalai-Nayar (2022), capacity constraints at the industry level can generate a convex Phillips curve and increase the welfare costs of business cycles. Similarly, IMF (2024) build a model with sectoral supply constraints (modeled through the labor market) which generates a non-linear Phillips curve relationship. Karadi et al. (2024) use a model similar to ours to study optimal monetary policy with a non-linear Phillips curve. Ball et al. (2022) estimate a price Phillips curve based on weighted median inflation and find significant coefficients on squared and cubed activity terms. Forbes et al. (2021) find empirical evidence of a non-linear Phillips curve using cross-country panel data. In contrast to these papers, the present study relates primarily to individual firms, taking the state of the aggregate economy as given, and does not assume any discontinuity in wage setting or demand beyond a s*ymmetric* menu cost. The kinked price Phillips curve at the firm level in our model arises endogenously from the interaction of menu costs, positive trend inflation, and decreasing returns. Its analogue at the aggregate level arises in a similar manner.

Our paper also relates to a long literature on how firms set prices reaching back to the 1970s. The more recent New-Keynesian literature typically uses a time-dependent approach to modeling how prices change, as in the model of Calvo (1983) where a subset of firms chosen randomly change prices at fixed intervals. The alternative state-dependent approach assumes that the decision to change prices depends on the state of the economy and the market faced by the firm; here, costs of changing prices (as in the menu cost models of Mankiw, 1985; Ball and Mankiw, 1994, 1995) create sticky prices or the cost of acquiring information about prices (as in Mankiw and Reis, 2002) prevents prices changing continuously. Several studies have sought to test these models using micro data, including Bils and Klenow (2004), Klenow and Kryvtsov (2008), and Nakamura and Steinsson (2008). Trying to better fit the empirical facts has led to these models being adapted, e.g. Golosov and Lucas Jr (2007) and Midrigan (2011). More recently Auclert et al. (2023) have argued that in low inflation environments (less than 5%) these models all give similar results, while Blanco et al. (2024) highlight important non-linearities in models that match both price change levels and frequencies.

A third literature uses micro data to highlight non-linear responses of prices to demand shocks, typically highlighting larger responses to positive than negative shocks. Peltzman (2000) studies item-level price changes in Dominick's supermarkets, showing prices rise faster in response to positive demand shocks than they fall in response to negative demand shocks. Buckle and Carlson (2000) examine survey data for New Zealand firms, again finding greater responsiveness to positive than negative demand shocks. Benzarti et al. (2020) show Finnish firms had twice the price response to value added tax rises than falls.

Finally, we also contribute to the growing literature on business surveys to evaluate the impact of major shocks we build on a recent growth literature, for example Altig et al. (2022), Bhandari et al. (2020) and Candia et al. (2023). The use of these large, high-frequency forward-looking firm surveys is valuable in this context because of the timely nature of the survey data, and in our case also because the survey has both forward and backward-looking aspects.

The structure of this paper is as follows. In Section 2, we show cross-country evidence of convexity in the relationship between inflation and economic slack. In Section 3 we provide more information on the Decision Maker Panel and the Survey of Business Uncertainty that we use. Section 4 presents three empirical tests of non-linearities in price-setting in response to demand shocks. Section 5 presents three extensions to the main results. In Section 6 we solve a general equilibrium menu cost model to rationalize our findings. Section 7 concludes.

2 Cross-country evidence on the price Phillips curve

We first analyze the relationship between aggregate inflation and economic slack in a cross-country panel dataset. Our approach is similar to Forbes et al. (2021), who estimate the Phillips curve using data for 31 countries over 1996-2017. We build on their approach, extending the sample up to 2023 for 38 countries. To perform this analysis, we collect data from three separate sources. First, we use data on headline consumer price index (CPI) inflation from the World Bank Global Database of Inflation (Ha et al. 2023).[9] Second, we collect data on CPI inflation forecasts from the IMF World Economic Outlook (WEO) historical forecasts database.[10] This dataset includes six years of forecast data for each country. For a given country-year there are two forecasts, from the Spring and Fall WEO, respectively. In the regressions we focus on five-year ahead forecasts for CPI inflation, $E_t[\pi_{it+5}]$, in order to capture long-run expectations, and we take the average of the two forecast vintages. Finally, for economic slack we use a measure of the 'output gap' based on estimates from the OECD. More precisely, this is estimated as the difference between actual GDP and potential GDP, as a percentage of potential GDP. Table A1 presents the list of countries and number of observations per country in our combined dataset. In sum, we have data for 38 countries over the period 1990-2023.[11]

We estimate the relationship between annual CPI inflation and economic slack using the following specification, estimated for country i and year t:

$$\pi_{i,t} = \alpha_i + \beta_t + \gamma\pi_{it-1} + \theta E_t[\pi_{it+5}] +$$

$$\lambda_1 OutputGap_{it} \times OG \geq 0 + \lambda_2 OutputGap_{it} \times OG < 0 + \varepsilon_{it}$$

The coefficients of interest are λ_1 and λ_2, which capture the relationship between the output gap and inflation, separately when the output gap is positive and negative. In addition, we include country fixed effects, α_i, which control for time-invariant differences across countries, such as different institutional frameworks or different average levels of inflation. We also

[9] Data can be accessed here: https://www.worldbank.org/en/research/brief/inflation-database
[10] Data can be accessed here: https://www.imf.org/en/Publications/WEO/weo-database/2024/April
[11] We exclude country-year observations with annual CPI inflation greater than 15% from the sample.

control for time fixed effects to account for large shocks which affect all countries. These include, for example, the Global Financial Crisis, Covid-19, and global changes in commodity prices. Finally, we control for lagged CPI inflation and five-year ahead inflation expectations, using data from the IMF WEO forecasts.

Figure 2 presents a binned scatterplot of headline CPI inflation against the output gap over the full sample. This figure visualizes the raw data, without any controls or fixed effects. We allow the slopes of the coefficients to vary when the output gap is positive and negative. There is clear evidence of a convex relationship in this figure: the coefficient on the positive output gap side is more than three times as large as the coefficient on negative output gap out-turns. In other words, years with output above potential are associated with stronger increases in aggregate inflation than periods when output is below potential. This is consistent with a non-linear price Phillips curve in the cross-country data.

In Table 1, we provide further robustness for this result. Columns 1-3 show the linear relationship between inflation and the output gap. This is positive and significant after controlling for country and time fixed effects (Column 2) as well as controls for lagged inflation and long-term inflation expectations (Column 3). Still, we note that the magnitude of the coefficient decreases with the inclusion of these controls. In Column 4, we add a quadratic term on the output gap. This is positive and significant, consistent with the convex relationship from Figure 2. In Column 5 we test this explicitly, by separating the slope coefficients depending on whether the output gap is positive or negative. We again find that the slope on the positive output gap is around three times larger (0.2) than the negative output gap (0.06). The row at the bottom of the table confirms that the difference between these coefficients is statistically significant at the 5% significance level.[12]

To what extent are these results driven by the pandemic and high-inflation episode since 2020? In Columns 6 and 7, we split the sample into 1990-2019 and 2020-2023, respectively. In both time periods, we find significant evidence of a non-linearity, with positive output gaps associated with much stronger aggregate inflation. Therefore, the convex relationship between inflation and economic slack is not a phenomenon solely of the recent exceptional shock, but also present in more ‘normal’ times. However, the non-linearity does appear to be stronger over

[12] To verify that our results are not driven entirely by this specific measure of economic slack, we construct an unemployment gap measure for this sample of countries. We construct this using an HP filter for each country’s unemployment series. In Figure A1, we find a similar non-linear relationship, with negative unemployment gap outturns associated with much stronger aggregate inflation than positive unemployment gap outturns.

2020-2023, consistent with a steepening of the Phillips curve over the recent years (see also IMF 2024).

It is important to emphasize that we do not make any structural or causal statements about the slope of the aggregate Phillips curve based on Table 1. There are multiple empirical challenges about estimating the Phillips curve using aggregate data, which are well-known in the literature.[13] First, the specification does not control for country-specific supply-side shocks which can affect both inflation and the output gap. Second, there is a debate about the appropriate variables to use, both on the right-hand side and the left-hand side of the specification. Different measures of inflation (e.g. headline CPI, core inflation, median CPI inflation) or slack (e.g. unemployment gap, output gap, vacancy-unemployment ratio) can lead to different conclusions. Finally, as argued by McLeay and Tenreyro (2019), monetary policy reacts endogenously to changes in demand, which can mask the true slope of the Phillips curve. In the following sections, we use data from large surveys of UK and US firms to assess the *causal* impact of demand shocks on firm prices and solve a general equilibrium model to study the implications for the aggregate Phillips curve.

3 Micro Data

We use data from two large, representative surveys of UK and US firms.

The Decision Maker Panel

The DMP is a large and representative online survey of Chief Financial Officers in UK businesses. The survey asks about recent developments and expectations for the year ahead in sales, prices, employment, and investment. An important advantage of the DMP survey relative to many other business surveys is the quantitative nature of the data that it collects. Bunn et al. (2024) provide a detailed overview of the survey, including the structure, quality checks against other datasets, and information on how to access the data.

The sampling frame for the DMP is the population of UK businesses with ten or more employees in the Bureau van Dijk FAME database.[14] It covers small, medium, and large private sector businesses across all industries. Firms are selected randomly from this sampling frame

[13] For example, Mavroeidis et al. (2014) and Hazell et al. (2022) all highlight the challenges of identifying Phillips curves in macro data while inflationary expectations, demand slack, and supply shocks are also changing.

[14] FAME is provided by Bureau Van Dijk (BVD) using data on the population of UK firms from the UK Companies House. FAME itself is part of the global AMADEUS database.

and are invited by telephone to join the panel by a recruitment team based at the University of Nottingham. This approach helps to ensure that the survey provides a representative view of the UK economy.[15] Once firms are part of the panel, they receive monthly emails with links to a five- to ten-minute online survey. Firms that do not respond to the survey for three consecutive months are re-contacted by telephone to check whether they received the emails or have other reasons for not completing the survey. When the DMP recruitment team first contact firms they ask to speak to the CFO, and failing that, the CEO, which is facilitated by the endorsement of the Bank of England. As a result, 79% of respondents are in these two positions (66% are CFOs and 13% are CEOs) with the remainder mostly senior finance managers. Given that the typical firm in the survey has about 75 employees, these CFOs and CEOs have a very good sense of the overall direction and performance of their business.

The DMP grew quickly after its launch and has averaged just under 2,500 responses a month since 2022, covering around 5% of UK private sector employment. The surveys have a rotating three-panel structure – each member is randomized at entry into one of the three panels (A, B or C). Each panel is given one third of the questions in any given month, so that within each quarter firms rotate through all questions. This helps keep the survey short for respondents whilst yielding a regular monthly flow of data. The response rate for active respondents is in the region of 50-55% and has only fallen back modestly since 2019 (Figure A2 shows the response rate and number of responses per month).

An important advantage of the DMP survey relative to other business surveys is the quantitative nature of the data that it collects. This makes the data particularly valuable for research, especially for analyzing the impact of major economic events such as the Covid pandemic where the scale of changes is large. Many other business surveys tend to focus on questions that ask businesses to indicate whether they expect the conditions that they face to get better or worse, rather than *by how much* they expect them to get better or worse. The reason that the DMP targets the CFOs (or CEOs) at these firms is because they are likely to be sufficiently numerate to respond to somewhat complex quantitative questions.

Since its inception, the DMP has asked firms about how the average price that they charge

[15] Figure A3 compares the distribution of firms in the DMP to the population of firms in the UK Interdepartmental Business register. The distribution across sectors is similar (Panel A) as well as the distribution across regions (Panel B). Aggregated results are always presented weighted by industry and employment shares.

has changed over the last year. The survey includes firms from across the economy, and therefore the pricing data are a mix of prices from consumer- and producer-facing businesses. Importantly, the DMP inflation data track the UK aggregate Consumer Prices Index and Producer Price Index inflation rates (Figure A4).

The survey also asks firms about their expectations for year-ahead inflation in their own average price. Rather than ask for a point estimate, respondents are asked about the distribution of expected possible outcomes. They are asked to provide their lowest, low, medium, high, and highest expectations for year-ahead inflation, and then for the probabilities associated with each scenario, where those probabilities must sum to 100% (see Figure A5 for screenshots of how this works in the survey). From this, it is possible to calculate a mean expected outcome, a standard deviation, and a skew. The survey also contains similar questions for sales, employment, and investment, allowing comparable metrics to be calculated for these variables. Although other related surveys such as the Atlanta Fed's Survey of Business Uncertainty have similar questions which allow measures of subjective uncertainty to be calculated for sales and employment, the DMP survey is the only one that has regularly asked this type of question about prices.

As well the regular questions on sales, prices, employment, and investment, the DMP survey also includes more ad-hoc questions about topical policy issues. Over the 2016-2022 period, these special questions focused on how Brexit and Covid have affected businesses.[16] More recently, questions have also been asked about price-setting behavior across firms (Bunn et al. 2023) and the impact of higher interest rates on businesses (Shah et al. 2024).

The Survey of Business Uncertainty

The Survey of Business Uncertainty (SBU) is a monthly online survey of CFOs and senior financial directors in US firms. It was established in 2014 and is organized by the Federal Reserve Bank of Atlanta in collaboration with Hoover Institution and Stanford University. The SBU is representative of the US economy by size and industry. The SBU panel is smaller than the DMP. As of August 2024, the SBU has around 2,200 panel members and receives around 1,000 responses each month. However, the structure of the survey and style of questions are very similar to the DMP: respondents are asked about current, past, and future outcomes for their business. They are also asked to provide subjective probability distributions for their

[16] Bloom et al. (2023) study the effects of Covid-19 on productivity using DMP data.

expectations (see Altig et al. 2022 for further details).

We use data from the SBU on the response of firm prices to hypothetical sales volume shocks. These were included in the survey in June 2024, and are identical to the questions asked in the DMP for comparability. However, questions on prices have not featured regularly in the SBU in the past. Therefore, the remainder of the empirical analysis in this paper after the hypothetical question is based on data from the DMP.

4 Firm price responses to demand shocks

In line with aggregate data, inflation within the DMP fell modestly during the first year of the Covid pandemic before picking up sharply thereafter (Figure A4). A key research question is whether this limited early pandemic disinflation and high subsequent inflation at least partly reflects convexities in price-setting behavior. Firms may respond in a non-linear manner to both demand shocks (such as the large fall in demand over 2020) or cost shocks (for example, the large energy price shock in 2022). In this section, we present three complementary results which all suggest firm prices are more responsive to positive versus negative demand shocks. In Section 5.3, we test for the presence of convexities in the response to costs shocks.

4.1 Hypothetical sales volume shocks and prices

The first approach we use to assess the responsiveness of firm prices to demand shocks is a randomized experiment within the survey. This is the cleanest setting to identify the causal impact of demand on prices. Over five months (December 2023 to January 2024 and August to October 2024), newly designed questions asked firms how their prices would respond to hypothetical sales *volume* shocks of different magnitudes.

The implementation took the following steps. First, firms were randomized into one of four shock scenarios: ±5%, ±10%, ±15%, and ±20%. They were then presented (at random) with the positive or the negative value of the shock and asked how they would adjust their price in response. Afterwards they were also asked about their response to an equivalent shock of the opposite sign. For example, a firm would be first asked if and how it would change prices in response to a -10% sales volume shock and then if and how it would change prices in response to a +10% sales volume shock. Figure A6 provides screenshots of the exact format of the questions in the survey platform. Over the five months, we received 3,197 responses from firms, which means 6,394 responses overall (two scenarios per firm).

In Figure 3 Panel A, we present the main result on hypothetical sales volume shocks from the DMP. This figure plots the average price response for each of the eight shock categories, with separate lines of best fit for positive and negative shock values. In doing so, we assume that a zero sales volume shock scenario corresponds to a zero price response (in other words, we estimate the lines of best fit without a constant). The figure suggests there is a clear non-linear relationship between sales shocks and price responses. For instance, an unexpected decline in sales by 20% leads to an average price decline of 0.14%. Meanwhile, a 20% *positive* sales volume shock leads to an average price increase of 1.2%. In general, the slope of the linear fit on the negative side is 0.007 (i.e. less than 1% pass-through); on the positive side it is 0.06 (i.e. around a 6% pass-through).

It may be that the convex response to sales volume shocks reflects something specific to UK firm price setting or the DMP survey. To address this, in June 2024, the identical question was implemented in the US by the Federal Reserve Bank of Atlanta in the Survey of Business Uncertainty (see also Meyer et al. 2024).[17] In total, 787 US firms responded to this question. Figure 3 Panel B presents the US result. There is again clear evidence of a convex relationship, with positive hypothetical sales volume shocks leading to stronger positive price responses. The responses across US and UK firms are also quantitatively very similar. In the regression analysis, we formally test for the significance of the difference in slopes.

In Table 2, we present the main results on the pass-through of sales volume shocks to prices. Columns 1-4 are the results for UK firms in the DMP. Column 1 presents the linear relationship: the coefficients suggests that a 1% increase in real sales volume would lead firms to increase prices by 0.03%. However, as suggested by Figure 3, this relationship is non-linear, with a stronger effect for positive sales shocks. In Column 2 we add a quadratic term, which is positive and highly significant, consistent with the presence of a convex relationship. In Columns 3-4, we explicitly test the difference in responses for negative versus positive shocks. Column 3 shows that there is no significant relationship between negative shocks and prices (with a slope coefficient of 0.007). Meanwhile, the response for positive shocks is stronger (0.06), and highly significant. Finally, below the coefficients we also test whether the difference between the two coefficients is statistically significant; indeed, we can reject the hypothesis that they are equal at 1% significance level. In Column 4 we estimate a similar regression, but weighting observations by industry and employment shares, and find that it does not affect our

[17] https://www.atlantafed.org/research/surveys/business-uncertainty

conclusions.[18]

Columns 5 to 8 of Table 2 present the corresponding results for US firms in the SBU. The results are very similar to those in the UK. In particular, Column 7 suggests that there is 9% pass-through of positive sales volume shocks to prices, whereas the pass-through of negative shocks is not statistically different from zero.[19] Overall, the results from Figure 3 and Table 2 provide robust evidence of a convexity between sales volume shocks and prices. In the next sub-sections, we show that firms respond in a convex manner not only to hypothetical scenarios, but also in their realized price setting. Due to data availability, the remaining empirical results are based only on UK firms in the Decision Maker Panel.

4.2 Evidence from sales and price growth forecast errors

To build on our findings using hypothetical shocks, in this section we consider the relationship between sales growth forecast errors and price growth forecast errors. This approach exploits the strong panel dimension of the DMP data. We calculate price growth (sales growth) forecast errors as the difference between annual own-price growth (sales growth) and expected year-ahead price growth (sales growth) that firms provided in their survey responses exactly one year earlier. Thus, the sample is firms who have provided survey responses in consecutive surveys 12 months apart.

Firm expectations are highly correlated with subsequent realizations, highlighting the quality of the forecast data (Figure A7). However, as firms experience unexpected shocks, their realizations may deviate from expectations, generating price and sales growth forecast errors.

We analyze the relationship between sales growth and price growth forecast errors, distinguishing between the effects of positive and negative sales errors. Figure 4 presents the main result. There is a strong positive relationship between the two series, with larger sales growth forecast errors (both positive and negative) associated with larger price growth forecast errors. Furthermore, there is a distinct non-linearity in this relationship, with a stronger relationship for positive rather than negative errors. The slope of this line (based on a regression without any fixed effects) suggests that a one percentage point larger positive sales growth error

[18] Across all three empirical exercises in this section, we test for the presence of convexity using a quadratic term and also by splitting the coefficients into positive/negative slopes. The results are similar with either approach, and we also note that the explanatory power is similar in both types of specifications. For ease of presentation, in the figures we present the versions with a kink at zero.

[19] The US figure 3b actually shows firms report price rises in response to negative sales shocks on average. This is consistent with a model of income targeting, where firms raise prices if sales fall to maintain a given revenue stream to cover fixed costs (e.g. Gilchrist et al. 2017).

is associated with a 0.1 percentage point larger price growth error (approximately a 10% pass-through). Meanwhile, the slope for negative sales growth errors is only 0.04. Overall, this figure provides further evidence that positive sales shocks have a distinctly stronger effect on price growth compared with negative shocks. We next test the robustness of this relationship, using fixed effects specifications and sample period splits.

In Table 3, we analyze in more detail the relationship between sales growth and price growth forecast errors. Column 1 confirms that there is a strong positive relationship between the two measures, which is highly significant at 1%. However, as suggested in Figure 4, there is likely a non-linearity in this relationship across positive versus negative errors.

Columns 2-5 test for the presence of a convexity in this relationship. Column 2 adds a quadratic term to the specification from Column 1, and the coefficient is found to be positive and highly significant. Across Columns 3-4, we find that the coefficients on positive sales growth forecast errors are larger than the coefficients on negative errors, in specifications without time or firm fixed effects (Column 3), and with those included (Column 4). In Column 4 (the most demanding specification with firm and time fixed effects), the coefficient on positive errors (0.075) is more than twice as large as the one on negative errors (0.035). Furthermore, as shown by the p-values at the bottom of the table, we are able to reject the hypothesis that the coefficients are equal with a high degree of confidence. Finally, in Column 5 we add an additional control for firm own-price expectations, to more closely match a firm-level Phillips curve specification. The non-linearity remains robust.

In addition to the main finding, which supports the non-linearity presented in Figure 4, we present several additional robustness checks. First, we check whether this is a COVID era phenomenon. To address this, in Columns 6-7 of Table 3 we split the sample into the periods 2018-2019 and 2020-2024. Although the sample size in the earlier period is only around one-fourth that of the latter period (due to the shorter time period and growing survey size), we still find evidence of non-linearities in both time periods. In the period 2018-2019, we again find that the coefficient on positive sales growth forecast errors is more than twice as large as that on negative errors, although the difference is only statistically significant at 20%, likely due to the smaller sample.

4.3 Demand shocks and price growth during the pandemic

The final test of price responses to demand shocks uses Covid-19 as a natural experiment. The Covid pandemic was a good example of a large and unexpected demand shock, and is therefore valuable for the study of how inflation responds to such shocks.[20] Starting in April 2020, soon after the start of the pandemic, firms in the DMP were asked to estimate how Covid-19 has affected their sales, relative to what otherwise would have happened.[21] We use this measure as a proxy of the 'Covid demand shock', conditional to other controls we can include in the regression specification.

Firms estimated that, on average, sales in 2020 Q2 were over 30% lower than they otherwise would have been because of Covid-19 as government restrictions were introduced (see Figure A8 for details). Since the middle of 2020, sales have recovered steadily, such that by 2022 Q2, firms were reporting that the level of sales was, on average, around 2% lower than they otherwise would have been. But these aggregate statistics mask significant heterogeneity across industries and firms where sectors that are more heavily dependent on face-to-face interaction with customers were hardest hit. This provides us with substantial variation to estimate the effects of changes in demand on inflation. On average between 2020 Q2 and 2022 Q2, 64% of respondents to the DMP survey reported that Covid-19 had lowered their sales, it had no impact for 19% of firms, and a positive impact for 16% of firms.

To examine the dynamics of realized inflation we estimate a set of firm-level regressions. These include own price inflation, $\pi_{i,t}$, as the dependent variable and firm-level measures of the Covid demand shock ($Y_{i,t}$), supply side factors ($S_{i,t}$), and expected year-ahead inflation ($E_t[\pi_{i,t+4}]$) as explanatory variables, as represented in equation 2. In this specification, i denotes the firm and t denotes the quarter. Unlike typical Phillips curve estimation, this relies more on variation across firms rather than over time. It will also exclude more general equilibrium channels that would be captured by an aggregate Phillips curve because it is estimated at the firm level but includes time effects. The equations also include firm fixed effects. The equations are estimated on a quarterly basis between 2017 Q1 and 2022 Q2 and are based on almost 35,000 individual data points for around 5,500 unique firms.

$$\pi_{i,t} = \alpha_i + \beta_t + \sigma Y_{i,t} + \omega S_{i,t} + \gamma E_t\left[\pi_{i,t+4}\right] + \varepsilon_{i,t} \qquad (2)$$

[20] Although the focus of this estimation is on the effects of Covid demand shocks, the pandemic has also affected the supply side of the economy (e.g. Brinca et al. (2021) and del Rio-Chanona et al. (2020) analyze the demand versus supply-side effects of Covid-19 in the US). In column 6 of Table 4, we control for several supply-side factors, such as the impact of Covid on firm costs, recruitment difficulties, and supply shortages, in order to test the robustness of our findings.

[21] The precise wording of the question is 'Relative to what would otherwise have happened, what is your best estimate for the impact of the spread of Covid-19 on the sales of your business in each of the following periods?'. Firms have typically been asked about the effects in the previous quarter and their expectations for the current quarter and next two quarters ahead. Realized data are used where available, but expectations or imputed estimates based on responses from earlier quarters are used where realized data are missing.

The first main result is that inflation responded asymmetrically to demand shocks during the pandemic. When sales were lowered, demand only had a small impact on inflation. But for firms that experienced a positive demand shock, the relationship between demand and inflation was significantly stronger. Figure 5 shows the relationship graphically.

Column 1 of Table 4 shows this result in regression form, without any additional fixed effects. The coefficient on the Covid impact on sales variable is significantly larger when the impact of Covid-19 on sales is positive than when it is negative. In column 2, we also include time fixed effects, and column 3 includes both time and firm fixed effects. The non-linearity is still clear and highly significant, although the coefficients move a little closer together than in column 1. In the last row of the table, we test for the statistical equality of the coefficients on the positive versus negative impact of Covid-19 on sales; in all cases, the difference is highly significant at the 1% level.

Columns 4 and 5 of Table 4 provide some more robustness checks on the asymmetry result. Column 4 shows how the non-linearity is not dependent on whether a control is included for whether the demand shock is positive or negative. In Column 5, instead of allowing the coefficient on Covid impact on price growth to vary according to the sign of that variable, we instead include a quadratic term. The coefficient on that squared term is positive and highly significant, meaning that the relationship between inflation and the Covid impact on sales is convex.

In Column 6 of Table 4 we introduce several supply-side factors that are likely to have affected inflation. The coefficients from all these additional controls are hidden in Table 4 for brevity but can be seen in Table A2. These variables largely represent changes in relative prices that would be likely to shift the position of the short-run Phillips curve rather than lead to movements along it. We include controls for Covid-related costs, supply and labor shortages, import intensity, energy prices, and additional costs relating to the end of the Brexit transition period.[22] The additional variables that we add in column 6 are from DMP questions where data is generally not available for all quarters.[23] Or in the case of energy intensity, we use two-digit industry level data from 2019. To address this, we calculate an average of each variable for each firm over the period in which data are available, and then allow the coefficient on that

[22] The control for Covid related costs represents the effect of Covid on the level of unit costs. This fits better than a cost growth term, implying that firms have continued to pass on higher costs in the later part of the pandemic despite cost growth turning negative. Figure A8 shows the data on Covid-related costs.
[23] So for example, the question on supply shortages was only included in the survey in October 2021.

time-invariant firm average to vary over time.[24] For brevity we only report results in Table A2 that interacted with a single time dummy (for 2021 Q2 to 2022 Q2 except for Covid-related costs, which is 2020 Q2 to 2022 Q2).

Including supply-side factors in Column 6 of Table 4 slightly reduces the coefficient on positive demand shocks, but a clear and statistically significant asymmetry in the response of inflation to positive and negative demand shocks remains. Covid-related costs, supply shortages, labor shortages, import prices, energy prices, and extra costs relating to the end of the Brexit transition period are all estimated to have had positive and statistically significant effects on inflation since 2021 Q2.

As well as measures of the business cycle and supply-side factors, aggregate Phillips curves also usually contain measures of expected aggregate inflation too. Ideally, we would include a firm level measure of expected aggregate CPI inflation. The data within the survey during this specific sample period is relatively short (it was introduced from May 2022), but we do have measures of expected own price inflation back to 2016. In column 7 we also add measures of lagged and expected own price inflation (the lagged term can help account for the fact expectations may be partially backward looking). Although the direction of causality is unclear using own price expectations, it shows how our other results are robust to the inclusion of the extra variable. Some of the coefficients become smaller, reflecting the fact these factors are also likely to be correlated with expected future inflation too.[25]

Summary of results Overall, this section analyzes how firm prices respond to demand shocks. The three empirical tests we use differ in the sample periods considered, and in the precise measurement of the shock and response components. In the first exercise (Section 4.1), we test the response of prices to hypothetical *sales volume* shocks using data from UK and US firms. This is arguably the cleanest setting in terms of identifying a causal impact. However, it may be that these responses do not correspond to pricing behavior in practice. To address this, in the second exercise (Section 4.2), we analyze price growth and nominal sales growth forecast

[24] This relies on the assumption that there is not substantial variation for a firm during the period over which we take averages. Indeed, the variation is relatively modest up to 2022Q2, which is the sample period for the regressions in this section.

[25] In the earlier working paper version of this paper (Bunn et al. 2022), we present several additional results on the asymmetric response of price inflation to the Covid demand shock. First, we show that the non-linearity is present for both goods producers and services providers. Second, we find evidence of an asymmetric response both in the first year of the pandemic, and separately, for the second year. The asymmetry is also not driven by firm liquidity, which would be consistent with the mechanism proposed by Gilchrist et al. (2017) for the financial crisis. Finally, we also show that the asymmetry is not driven by positive shocks being perceived as more persistent by firms, which could explain the stronger price response.

errors. This uses the longest sample period available and reflects real-world price expectations and realizations. However, it may still be that forecast errors are influenced by mismeasurement or omitted variables beyond what we capture using controls and fixed effects, and it relies on sales values rather than the ideal measure of sales volumes.[26] For further robustness, in the final exercise (Section 4.3), we test how firm price growth responds to the impact of Covid-19 on firm (nominal) sales, which was a large unexpected demand shock, but also a unique period. Despite the limitations of each individual exercise, we find robust evidence of a non-linearity in all three cases, with stronger price responses to positive shocks. The results are not only qualitatively but also quantitatively similar to each other. In Section 6, we show that a model with menu costs, trend inflation, and decreasing returns at the firm level can match our firm-level results. In the next section, we provide three additional empirical extensions, which also help motivate our modelling approach.

5 Extensions

In the previous section, we presented evidence that firm prices respond by much more to positive demand shocks compared with negative demand shocks using three separate empirical exercises. There are multiple mechanisms which can explain this non-linear firm-level response, including potentially capacity constraints (e.g. Boehm and Pandalai-Nayar 2020), financial constraints (e.g. Gilchrist et al 2017), or non-linear demand functions (e.g. Harding et al. 2023). In this section, we present three extensions to our main results which will be important in the model section for identifying a menu cost channel for convex price responses. In Section 6 we outline our general equilibrium model which we will use to match the main results as well as these extensions.

5.1 High vs. low inflation

In the first extension, we consider whether the convexity we capture is stronger in periods of higher inflation. Our modeling framework (detailed in Section 6) would predict that when ‘trend’ inflation is higher, firms are more likely to pay the menu cost and increase their prices following positive demand shocks than cut prices following negative shocks.

To test this in the data, we calculate the average price growth for each firm across all survey waves. We then split firms by whether their average price growth is above or below the

[26] The use of sales values rather than volume should not be able to explain why firm prices respond more to positive demand shocks than negative ones.

full sample average of 4% for all firms. High-inflation firms (those above 4%) have had an average price growth around 7%, whereas the average for low-inflation firms (those below 4%) is 1.5%.

In Figure 6, we present the results on the three empirical exercises from Section 4, separately for high-inflation and low-inflation firms. In all three panels, we find evidence of a clear convexity for high-inflation firms (top row). Meanwhile, for low-inflation firms (bottom row) the evidence suggests a much more linear pass-through of demand shocks to prices. We next test this formally in a regression table.

In Table 5, we provide further robustness for the results in high vs. low inflation firms. Columns 1 and 2 present the results using the hypothetical sales volume shocks. In both columns there is evidence of non-linearity, although this is much stronger (both in statistical significance and difference between positive and negative coefficients) for high-inflation firms. Columns 3 and 4 show the results for sales and price forecast errors, also controlling for firm and time fixed effects. The convexity remains pronounced and highly significant for high-inflation firms (Column 3), whereas for low inflation firm (Column 4), the difference between the coefficients is not statistically significant. In Columns 5 and 6, we use the same sample splitting approach and show that the price response to the Covid demand shock displays a significant non-linearity, but only in high-inflation firms.

One concern with the above approach may be that we are splitting firms by the dependent variable when we separate into high versus low inflation, therefore creating some endogeneity. As an alternative, we measure the average price growth at the sector-year level in our dataset. Specifically, we use detailed SIC3 sectors, of which there are 262 in the sample. We compute this separately for each firm i, such that the sectoral average will *exclude* that firm from the calculation (a "leave-one-out" approach). We also compute the average yearly price growth across all firms in the sample, and we then split firms according to whether their sector is above or below the sample average in a given year. In this way, a given sector can have above-average price growth in one year, but below-average price growth in another. We again find strong evidence of a non-linearity in high-inflation sectors, while in low-inflation sectors we cannot reject the null of linear pass-through (Table A3).

Overall, we conclude from this sub-section that the inflation rate is an important determinant for the convexity in the price response to demand shocks. This is particularly important for policymakers to consider when inflation is elevated – in such cases, prices can become much more responsive to positive shocks.

5.2 Longer-run responses

The empirical analysis so far has focused on the response of firm prices to shocks over the short-term. Doing this, we find strong evidence that the response to positive shocks is stronger that the response to negative shocks. In this subsection, we explore how these responses evolve over time, again utilizing the panel dimension of the dataset. Specifically, for each firm, we calculate the *cumulative* sales growth and cumulative price growth (not the forecast errors of these quantities) over horizons from one to four years.[27] We then estimate the relationship between sales growth and price growth at each horizon, separating the coefficients by whether the cumulative sales growth is positive or negative.

Figure 7 presents the main results from this exercise by plotting the coefficient estimate for positive and negative cumulative sales growth with 90% confidence intervals. The first set of coefficients plotted at the year 1 horizon is similar to our main result from Figure 4 that was based on forecast errors: positive sales growth over one year has a stronger correlation with annual price growth (roughly twice as large) than negative sales growth. However, when we consider the evolution of the coefficients by extending the horizon to 2, 3 and 4 years, we find that the coefficient estimates converge, with the effects of negative growth catching up with those on positive cumulative sales growth. By the three-year horizon the coefficients are not significantly different, and by the four year horizon the point estimates are essentially identical. Thus, negative sales growth does not lead to a *permanently* lower response in prices; rather that the path of adjustment is different. The evidence suggests that that despite the initial non-linearity, over a longer time horizon, the effects are identical.

Table 6 presents the results from Figure 7 in a regression form. Columns 1-4 show the results for each of the four horizons. The last row of the table tests for the equivalence of the coefficients on positive and negative sales growth. As suggested by the figure, we can reject the equivalence over the first and second year. However, by the third and fourth year, the difference is no longer statistically significant, and in Column 4, the coefficient estimates are almost identical. Columns 5-6 show that these results do not change when adding firm (Column 5) or firm and time (Column 6) fixed effects to the specification from Column 4.

[27] Firms are not asked about expected sales or price growth beyond the one-year horizon, therefore it is not possible to construct longer-run forecast errors in the way we construct them for the one-year horizon.

5.3 Prices and costs

So far, the analysis has focused on the response of prices to demand shocks, measured in several different ways. However, it is also important to consider how firms set prices in response to *cost* shocks, for at least two reasons. First, the standard New Keynesian Phillips curve models prices at the firm level as a mark-up over marginal cost. Marginal costs are notoriously difficult to measure, and the literature therefore usually focuses on average or unit costs, or estimates derived from assumed production functions, in this estimation. Second, the recent inflation episode over 2022-2024 has been driven in large part by cost shocks.

Intuitively, cost shocks should affect price decisions in a similar way to demand shocks, by moving a firm's optimal price away from its current value. In a menu cost model, positive cost shocks move firms closer to their price-increase thresholds, causing them to increase prices. Trend inflation makes the price increase and decrease thresholds asymmetric, and firms are *less* likely to lower prices following negative shocks. This should make the price response convex in response to cost shocks. In this sub-section, we empirically test the response of firm prices to unit cost shocks using two separate empirical exercises.

Hypothetical unit costs shocks

We first analyze how firms respond to cost shocks using a randomized survey experiment conducted over August to October 2024. Similar to our setup for sales volume shocks (see Section 4.1), we randomly assign firms to one of four scenarios, which differ in the magnitude of the hypothetical unit cost shock they receive: ±5%, ±10%, ±15%, and ±20%. Firms are asked about their response to both the positive and negative unit cost shocks. Firms are also randomized into whether they first receive the positive or the negative scenario (Figure A9 shows the precise question). Over the three months, 1,864 firms responded to the hypothetical scenarios, which gives 3,728 observations in total (two scenarios per firm).

Figure 8 plots the average (unweighted) response to these unit cost shocks scenarios. We estimate the lines of best fit using a regression with no constant, such that a 0% unit cost shock corresponds to a 0% average price response. Firms respond significantly to both positive and negative shocks, but we again note a significant non-linearity. The response to positive shocks is around 0.6, or a 60% pass-through. Meanwhile, the response to negative shocks is only 0.2, meaning 20% pass-through.

In Table 7, we provide further evidence for the robustness of the responses to hypothetical cost shocks. The convexity is present using a quadratic term in Column 2, and furthermore we can reject with high level of confidence the equality of the coefficients on positive vs. negative unit cost shocks (Columns 3-4). Overall, this exercise provides evidence that cost shocks are passed through in a non-linear fashion to firm prices. This is important to bear in mind, especially when an economy is hit by large shocks. On the one hand, assuming a linear pass-through of shocks can underestimate how quickly prices will rise following cost increases. Equally, a linear pass-through would over-estimate how quickly price growth declines as cost shocks unwind.[28]

Price growth and unit cost growth forecast errors

A second approach to measure the pass-through of cost shocks to firm prices is using forecast errors. Questions on realized annual unit cost growth and expected year-ahead unit cost growth have been asked in the DMP survey, although less frequently compared to the questions on sales growth. Nevertheless, there are enough observations to construct unit cost growth forecast errors for part of the sample.[29] These errors are fairly evenly distributed in the sample, with an average error of 0.13 percentage points.

In Figure 9, we present a binned scatterplot of the relationship between unit cost growth forecast errors and price growth forecast errors. Consistent with the evidence from the hypothetical unit cost shocks, we find evidence of a non-linearity in the effects of positive vs. negative cost errors. On the positive side, a one percentage point cost error is associated with a 0.4 percentage point price growth error (i.e. 40% pass-through). The coefficient on the negative cost errors is around one-third in magnitude, suggesting only 14% pass-through.

In Table 8, we show the main results on unit cost and price growth forecast errors. Column 3 replicates the results from Figure 9 without fixed effects, and we can reject the hypothesis that the two coefficients as equal. In Columns 4-5 we add firm and time fixed effects to the specification. The decreases the sample to less than 1,000 observations, because the data on unit cost growth forecast errors is available only for a short sample.[30] It also means we are

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[28] There is also evidence from the US that firm prices respond asymmetrically to cost shocks. In a blog post from 2013, Mike Bryan, Brent Meyer and Nicholas Parker show qualitative evidence that firms in the Atlanta fed Business Inflation Expectations (BIE) survey are more likely to increase prices following rises to raw material costs than they are to decrease prices following declines in costs. When costs decline, firms indicate that they are more likely to increase profit margins.

[29] Specifically, we can construct unit cost growth forecast errors for February-April 2018, May-July 2023, and May-July 2024.

[30] The available firm observations for this exercise is also reduced because the questions on own-price growth

no longer able to reject the null that the coefficients on positive and negative errors as significantly different. However, we note that the magnitude of the coefficients does not change much when including these fixed effects, and indeed only the effect of positive cost growth errors is statistically different from zero. Despite these data limitations, the evidence on forecast errors is also consistent with a non-linear pass-through of cost shocks to prices, with the response to positive shocks around three times as strong as the response to negative shocks.

Summary of results Overall, this section provides several extensions to our main results from Section 4. We show that: (i) the convex response to demand shocks is driven by firms with high own-price inflation; (ii) this convexity is pronounced at the one-year horizon, but over time the responsiveness to positive and negative shocks equalizes; and (iii) there is a similar non-linearity of firm prices in response to unit cost shocks, with pass-through around three times as strong when costs increase. In the next section, we solve a general equilibrium menu cost model to rationalize our findings and analyze the implications for aggregate inflation dynamics.

6 DSGE model

The empirical work so far has presented evidence consistent with a convex aggregate Phillips curve (Section 2) and significant evidence of non-linear pass-through of demand shocks to prices using survey data from UK and US firms (Sections 4 and 5). In this section we set out a menu cost model that rationalizes our main firm-level findings and we use it to study the implications for the aggregate Phillips curve. Using a model is crucial, as general equilibrium effects can affect how individual firm responses aggregate to the macro level (see, for example, Hazell et al. 2022, on the importance of taking general equilibrium effects into account).

6.1 Model structure

Our model is based closely on Nakamura and Steinsson (2010).[31] What follows is an abbreviated description of the model, with particular emphasis on the modifications we make. First, the production technology of firms exhibits decreasing returns to scale at the firm level,

and unit cost growth are asked in separate panels. Therefore, although we have 2,941 cost growth forecast error observations, we have matching price growth forecast errors for only 1,621 observations.

[31] We choose to adopt a menu cost price-setting model from the literature based on answers to survey questions in the DMP. In 2023 and 2024, firms were asked whether they usually set prices at fixed intervals (i.e. ‘time-dependent’ price setting) or in response to events (i.e. ‘state-dependent’). In both years, the majority of firms selected state-dependent price-setting, as shown in Figure A10.

but returns to scale are constant at the aggregate level. Second, firms are subject to idiosyncratic demand shocks, in addition to aggregate demand shocks as in the original Nakamura and Steinsson (2010) model.

There is a continuum of firms indexed by z, each of which produces a single differentiated good $y_t(z)$ using a diminishing returns to scale (DRS) production technology using labor and intermediates, where λ indexes the degree of decreasing returns:

$$y_t(z) = A_t(z)\left[L_t^{1-s_M}(z)M_t^{s_M}(z)\right]^{\lambda}$$

where $A_t(z)$ is labor productivity and $M_t(z)$ is an index of intermediates. Products are both intermediates and final goods in roundabout production as in Nakamura and Steinsson (2010). Productivity is an AR(1) process, independent and mean zero across firms:

$$\log(A_t(z)) = \rho \log(A_{t-1}(z)) + \varepsilon_t(z)$$

Consumers maximize utility over compositive consumption C and labor supply L:

$$E_t \sum_{\tau=0}^{\infty} \beta^{\tau} \left[\frac{1}{1-\gamma} C_{t+\tau}^{1-\gamma} - \frac{\omega}{\varphi+1} L_{t+\tau}^{1+\varphi}\right]$$

Consumers have isoelastic preferences over each of the varieties, such that firms face the following demand curve:

$$c_t(z) = C_t \left(\frac{p_t(z)}{P_t}\right)^{-\theta} d_t(z)$$

where $d_t(z)$ is an idiosyncratic preference shock that generates variation in demand at the firm level, and where $p_t(z)$ and P_t are the firm's price and the aggregate price level respectively. Firms can change their nominal price if they hire κ units of labor, such that their per-period profits are given by:

$$\pi_t(z) = p_t(z)y_t(z) - \frac{W_t(z)}{P_t}\big(L_t(z) + \kappa I_t(z)\big)$$

Firms maximize the present discounted value of these profits, discounted at consumers' stochastic discount factor. The firm-level idiosyncratic demand shock $d_t(z)$ follows an AR(1) process:

$$d_t(z) = \rho_d d_{t-1}(z) + \varepsilon_t^d(z)$$

Aggregate demand S_t follows a random walk with drift:

$$S_t = \mu + S_{t-1} + \eta_t$$

There is no long-run growth in productivity or labor supply in the model so μ equals the average inflation rate. The model is closed with market clearing for goods and labor, with roundabout production.

6.2 Calibration, solution, and simulation method

Where possible and except where stated otherwise, our calibration follows that of the one-sector menu-cost model in Nakamura and Steinsson (2010). Table 9 summarizes all the model parameters. We calibrate demand shocks to have the same persistence and baseline variance as productivity shocks in Nakamura and Steinsson (2010). To solve the model, the state and choice spaces are discretized on grids. We solve the firm's decision problem by iteration on the value function based on a guess of the aggregate law of motion $E_t[P_{t+1}] = \Gamma\left[\frac{S_t}{P_t}\right]$. We then update this guess for Γ based on the aggregate dynamics that result from our solution to the firm's problem. We iterate this procedure until convergence, checking that the final solution Γ is reasonably accurate and unbiased. To produce our simulated data, we simulate 1000 firms for 100 years (1200 periods of one month).

6.3 Baseline results

In this subsection of the paper, we perform the same empirical exercises on our simulated data as we did on the DMP data. First, we analyze the firm-level price responses to positive versus negative demand shocks.

The results from the firm-level simulated data are presented in Figure 10, Panel A. As with the empirical results presented in Section 4, we find evidence of a distinct non-linearity. Positive demand shocks lead to stronger price inflation at the firm level; negative demand shocks decrease price growth by much less.

In Figure 10, Panel B we aggregate the firm-level responses to generate the standard Phillips curve relationship. We find strong evidence that the aggregate Phillips curve is also convex. The non-linearity we observe at the firm level therefore survives aggregation and the incorporation of general equilibrium effects.

6.4 Extension results

In ongoing analysis, we use the model to test that these convexities are more pronounced in economies with higher inflation and absent in an economy with no trend inflation. We also test that these convexities dissipate over time, so that the long-run response to positive and negative demand shocks is symmetric. Finally, we test that the price response to cost shocks (modelled as productivity shocks) is also convex due to the similar Ss intuition under trend-inflation as drives the convex response to demand shocks.

7 Conclusion

Inflation rates across many advanced economies reached levels not seen for decades following the exceptional economic shocks of the Covid-19 pandemic and the war in Ukraine. This stimulated a renewed interest in studying price-setting behavior and potential convexities in the Phillips curve. Convexities in the relationship between inflation and economic slack are present in cross-country macro data, although identification in these settings is an established empirical challenge. In this paper, we use firm-level data from large representative surveys of US and UK firms to test for non-linearities in the response of firm prices to shocks.

We carry out three different empirical exercises which all show that prices respond in a non-linear way to demand shocks. First, we use a randomized survey experiment where firms indicate their price responses to a series of hypothetical sales volume shocks. The effect of positive shocks is estimated to be significantly stronger than the response to negative shocks. To substantiate these findings using data on real price-setting, we test the relationship between sales growth and price growth forecast errors, leveraging the strong panel dimension of the survey. The results again suggest a significant convexity, with positive sales growth forecast errors associated with price growth forecast errors which are at least twice as large. Finally, we use Covid-19 as a natural experiment and show that inflation was five times more sensitive to demand when demand was growing than when it was falling. This non-linear relationship between demand and inflation can help to explain why inflation only fell modestly during the first year of the Covid pandemic but accelerated during the demand rebound.

Many models can generate convex responses of prices to demand shocks at the firm level, including menu-costs, capacity constraints, financial constraints, and non-linear demand curves. To make progress identifying between these we extend these results in three ways. First, we show that the convex response to demand shocks is pronounced when inflation is high. Second, we show that the non-linearities are a short-term phenomenon: over longer time horizons (more than three years), the responses to positive and negative sales growth converge. Thirdly, we show that firms also respond in a non-linear fashion to cost shocks, with pass-through around three times stronger for increases in costs.

Finally, we build a model of price-setting behavior which features menu costs, trend inflation, and diminishing returns at the firm level. Simulated data from the model are able to replicate the main firm-level convexity in prices, and a convex *aggregate* Phillips curve in response to demand shocks. Furthermore, it can also match out additional empirical results. The model generates greater convexity at higher levels of inflation, linearity over long-run horizons, and convexity in the price response to cost shocks.

Our results highlight the importance of taking asymmetries in pricing behavior into consideration, both in empirical and theoretical work.

8 References

Altig, D, S Baker, J M Barrero, N Bloom, P Bunn, S Chen, SJ Davis, J Leather, BH Meyer, E Mihaylov, P Mizen, N Parker, T Renault, P Smietanka and G Thwaites (2020), "Economic Uncertainty Before and During the COVID-19 Pandemic", *Journal of Public Economics*, 191, article 104274.

Altig, D, J M Barrero, N Bloom, S J Davis, B H Meyer, and N Parker, (2022), "Surveying Business Uncertainty", *Journal of Econometrics* 231(1): 282-303.

Alvarez, F, H Le Bihan and F Lippi (2016), "The real effects of monetary shocks in sticky price models: A sufficient statistic approach", *The American Economic Review* 106(10): 2817-2851.

Anayi, L, N Bloom, P Bunn, P Mizen, G Thwaites and I Yotzov (2022), "The impact of the war in Ukraine on economic uncertainty", VoxEU.org, 16 April.

Auclert, A, R Rigato, M Rognlie and L Straub, (2023), "New pricing models, same old Phillips curves?", Quarterly Journal of Economics, 121-186.

Ball, L and N G Mankiw (1994), "Asymmetric price adjustment and economic fluctuations", *The Economic Journal* 104(423): 247-261.

Ball, L and N G Mankiw (1995), "Relative-price changes as aggregate supply shocks", *The Quarterly Journal of Economics* 110(1): 161-193.

Ball, L, D Leigh and P Misha (2022), "Understanding US inflation during the Covid era", NBER Working Paper 30613.

Baqaee, D and E Farhi (2022), "Supply and demand in disaggregated Keynesian economies with an application to the COVID-19 crisis", *American Economic Review* 112(5): 1397-1436.

Bartik, A, M Bertrand, Z B Cullen, E L Glaeser, M Luca, and C Stanton, (2020), "The Impact of COVID-19 on Small Business Outcomes and Expectations", *Proceedings of the National Academy of Sciences*, 117, no 30.

Benigno, P and G B Eggertsson (2023), "It's baaack: The surge in inflation in the 2020s and the return of the non-linear Phillips curve", NBER Working Paper 31197.

Benigno, P and G B Eggertsson (2024), “The slanted-L Phillips curve”, NBER Working Paper 32172.

Benzarti, Y, D Carloni, J Harju and T. Kosonen (2020), “What goes up may not come down: asymmetric incidence of value-added taxes”, Journal of Political Economy,

Beraja, M, E Hurst and J Ospina (2019), “The Aggregate Implications of Regional Business Cycles”, *Econometrics* 87(6): 1789-1833.

Bhandari, A, S Birinci, ER McGrattan, and K See, (2020), “What Do Survey Data Tell Us about US Businesses?”, *AER: Insights*, 2(4): 443–458.

Bils, M and P J Klenow (2004), “Some evidence on the importance of sticky prices”, *Journal of Political Economy* 112(5): 947-985.

Blanco, A, Corina Boar, Callum Jones and Virgiliu Midrigan, (2024), “Non-linear dynamics in menu-cost economies? Evidence from US data”, NBER Working paper 32748.

Bloom, N, P Bunn, P Mizen, P Smietanka and G Thwaites (2023), “The impact of Covid-19 on productivity”, *Review of Economic Statistics*, 1-45.

Bloom, N, M Floetotto, N Jaimovich, I Saporta-Eksten and S J Terry (2018), “Really uncertain business cycles”, *Econometrica* 86(3): 1031-1065.

Boehm, C E and N Pandalai-Nayar (2022), “Convex supply curves”, *American Economic Review* 112(12): 3941-3969.

Bonam, D and A Smădu (2021), “The long-run effects of pandemics on inflation: Will this time be different?”, *Economics Letters* 208 (110065).

Brinca, P, J B Duarte and M Faria-e Castro (2021), “Measuring labor supply and demand shocks during Covid-19”, *European Economic Review* 139, 103901.

Brodeur, A, D Gray, A Islam and S Bhuiyan, (2021), “A literature review of the economics of Covid-19”, *Journal of Economic Surveys* 35 (4), pp 1007-1044.

Brynjolfsson, E, J Horton, A Ozimek, D Rock, G Sharma, and H TuYe, (2020), “Covid-19 and Remote Work: An Early Look at US Data”, NBER Working Paper 27344.

Buckle, R and John Carlson (2000), “Inflation and asymmetric price adjustment”, *Review of Economics and Statistics*, 157-160.

Bunn, P, L Anayi, N Bloom, P Mizen, G Thwaites and I Yotzov (2022), “Firming up price inflation”, Bank of England Staff Working Paper 993.

Bunn, P, N Bloom, P Mizen, O Ozturk, G Thwaites and I Yotzov (2023), “Price-setting in a high-inflation environment”, VoxEU.org, 7 August.

Bunn, P, N Bloom, A Crundwell, S Khan, C Menzies, P Mizen, M Sculthorpe, K Shah, G Thwaites and I Yotzov (2024), “The Decision Maker Panel: A User’s Guide”, Bank of England Staff Working Paper 1096.

Cajner, T, L D Crane, R A Decker, J Grigsby, A, Hamins-Puertolas, E Hurst, C Kurz, and A Yildirmaz, (2020), “The US Labor Market during the Beginning of the Pandemic Recession” NBER Working Paper 27159.

Calvo, G A (1983), “Staggered prices in a utility-maximizing framework”, *Journal of Monetary Economics* 12(3): 383-398.

Candia, B, O Coibion and Y Gorodnichenko (2023), “The Macroeconomic Expectations of Firms”, In *Handbook of Economic Expectations*, pp. 321-353, Elsevier.

Chetty, R, J Friedman, N Hendren, and M Stepner, (2020), “The Economic Impacts of Covid-19: Evidence from a New Public Database Built Using Private Sector

Data", NBER Working Paper 27431.
Criscuolo, C, (2021), "Productivity and Business Dynamics through the lens of Covid-19: the shock, risks and opportunities", ECB SINTRA Paper, pp 1-82.
Daly, K and R Chankova (2021), "Inflation in the aftermath of wars and pandemics", Goldman Sachs Global Economics Analyst, 25 March.
Davies, R (2021), "Prices and inflation in a pandemic – a micro data approach", Centre for Economic Performance Covid-19 Analysis Series No. 017.
Del Rio-Chanona, R M, P Mealy, A Pichler, F Lafond and J D Farmer (2020), "Supply and demand shocks in the Covid-19 pandemic: An industry and occupation perspective", *Oxford Review of Economic Policy* 36(Supplement 1): S94-S137.
Fitzgerald, Terry J., Callum Jones, Mariano Kulish, and Juan Pablo Nicolini, (2020) "Is There a Stable Relationship between Unemployment and Future Inflation?," Federal Reserve Bank of Minneapolis Working Paper.
Forbes, K, J Gagnon and C G Collins (2021), "Low inflation bends the Philips curve around the world", NBER Working Paper 29323.
Forsythe, E, LB Kahn, F Lange, and D G Wiczer, (2020), "Labor Demand in the Time of COVID-19: Evidence from Vacancy Postings and UI Claims", *Journal of Public Economics*, Vol 189.
Gilchrist, S, R Schoenle, J Sim and E Zakrajšek (2017), "Inflation dynamics during the financial crisis", *American Economic Review* 107(3): 785-823.
Golosov, M and R E Lucas (2007), "Menu costs and Phillips curves", *Journal of Political Economy* 115(2): 171-199.
Guerrieri, V, G Lorenzoni, L Straub and I Werning (2022), "Macroeconomic implications of Covid-19: Can negative supply shocks cause demand shortages?", *American Economic Review* 112(5): 1437-1474.
Ha, J, A Ayhan Kose and F Ohnsorge (2023), "One Stop Source: A Global Database of Inflation", *Journal of International Money and Finance* 137 (October): 102896.
Harding, M, J Linde and M Trabandt (2023), "Understanding post-Covid inflation dynamics", *Journal of Monetary Economics*.
Hazell, J, J Herreno, E Nakamura and J Steinsson (2022), "The Slope of the Phillips Curve: Evidence from U.S. States", *The Quarterly Journal of Economics* 137(3): 1299-1344.
IMF (2024), "The Great Tightening: Insights from the Recent Inflation Episode", Chapter 2, World Economic Outlook, October 2024.
Jordà, Ò, S R Singh and A M Taylor (2022), "Longer-run consequences of pandemics", *The Review of Economics and Statistics* 104(1): 166-175.
Kalemli-Ozcan, S, P-O Gourinchas, V Penciakova and N Sander (2020), "Covid-19 and SME failure", IMF Working Papers 2020(207).
Karadi, P and A Reiff (2019), "Menu costs, aggregate fluctuations, and large shocks", *American Economic Journal: Macroeconomics* 11(3): 111-146.
Karadi, P, A Nakov, G Nuno, E Pasten and D Thaler (2024), "Strike while the Iron is Hot: Optimal Monetary Policy with a Nonlinear Phillips Curve", CEPR Discussion Paper 19339.
Khan, A and J K Thomas (2008), "Idiosyncratic shocks and the role of non-convexities in plant and aggregate investment dynamics", *Econometrica* 76(2): 395-436.

Klenow, P J and O Kryvtsov (2008), "State-dependent or time-dependent pricing: Does it matter for recent U.S. inflation?", *The Quarterly Journal of Economics* 123(3): 863-904.

Mankiw, N G (1985), "Small menu costs and large business cycles: A macroeconomic model of monopoly", *The Quarterly Journal of Economics* 100(2): 529-538.

Mankiw, N G and R Reis (2002), Sticky Information versus Sticky Prices: A Proposal to Replace the New Keynesian Phillips Curve" *The Quarterly Journal of Economics,* 117(4), 1295–1328

Mavroeidis, Sophocles, Mikkel Plagborg-Møller, and James H. Stock, (2014) "Empirical Evidence on Inflation Expectations in the New Keynesian Phillips Curve," *Journal of Economic Literature*, 52, 124–188.

McLeay, M and S Tenreyro (2019), "Optimal inflation and the identification of the Phillips curve", *NBER Macroeconomics Annual* 34.

Meeks, R and F Monti (2023), "Heterogeneous beliefs and the Phillips curve", *Journal of Monetary Economics*.

Midrigan, V (2011), "Menu costs, multiproduct firms, and aggregate fluctuations", *Econometrica* 79(4): 1139-1180.

Nakamura, E and J Steinsson (2008), "Five facts about prices: A reevaluation of menu cost models", *The Quarterly Journal of Economics* 123(4): 1415-1464.

Nakamura, E and J Steinsson (2010), "Monetary non-neutrality in a multisector menu cost model", *The Quarterly Journal of Economics* 125(3): 961-1013.

Papanikolaou, D, and L D W Schmidt, (2020), "Working Remotely and the Supply-side Impact of Covid-19", NBER Working Paper 27330.

Peltzman, S, (2000), "Prices rise faster than they fall", *Journal of Political Economy*. pages 466-502.

Phillips, A W (1958), "The relation between unemployment and the rate of change of money wage rates in the United Kingdom, 1861-1957", *Economica* 25(100): 283-299.

Salgado, S, F Guvenen and N Bloom (2023), "Skewed business cycles", Working Paper.

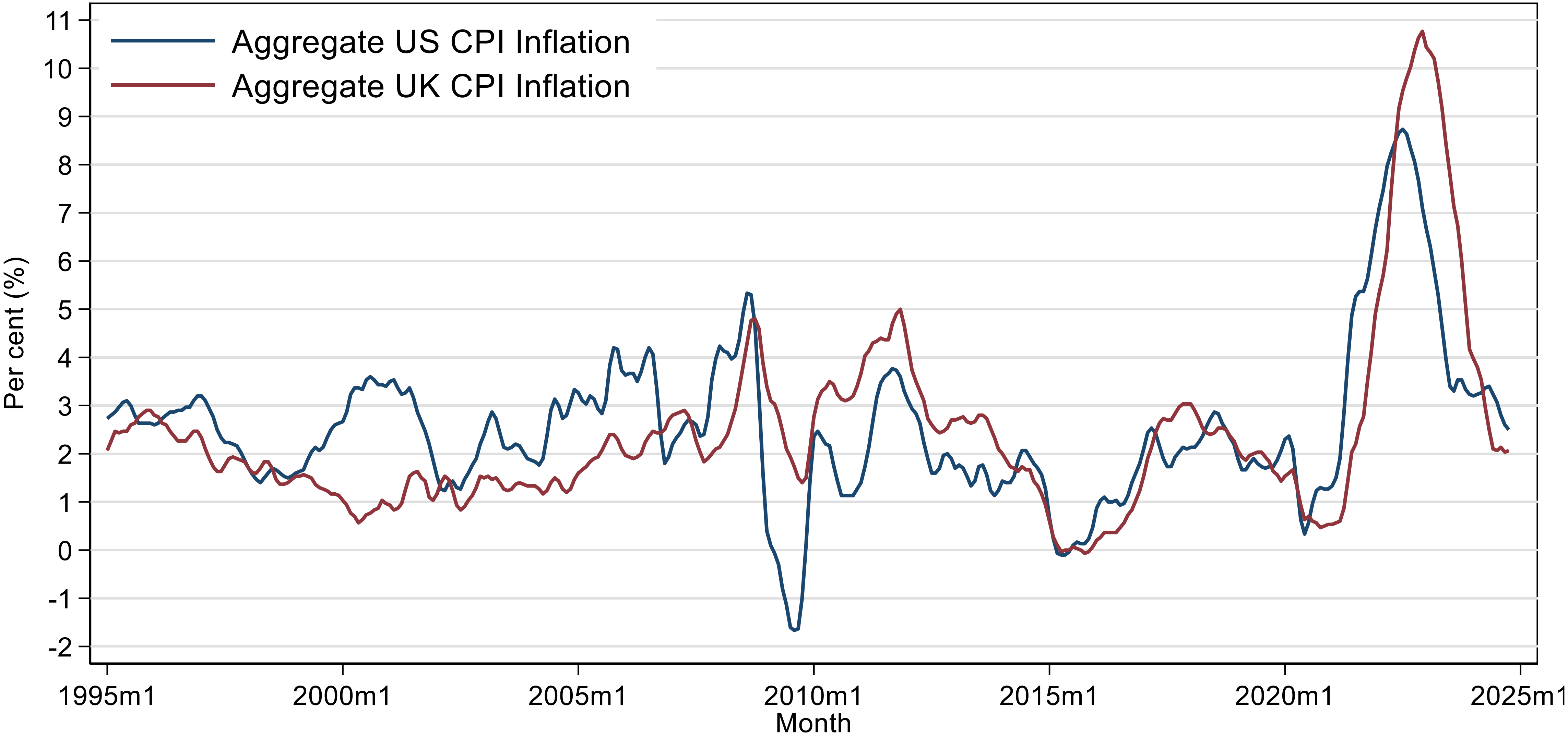
Shah, K, N Bloom, P Bunn, P Mizen, G Thwaites and I Yotzov (2024), "The impact of higher interest rates on UK firms", VoxEU.org, 26 April.

Werning, I (2022), "Expectations and the rate of inflation", NBER Working Paper 30260.

Yotzov, I, L Anayi, N Bloom, P Bunn, P Mizen, O Ozturk and G Thwaites (2023), "Firm inflation uncertainty", *AEA Papers and Proceedings* 113.

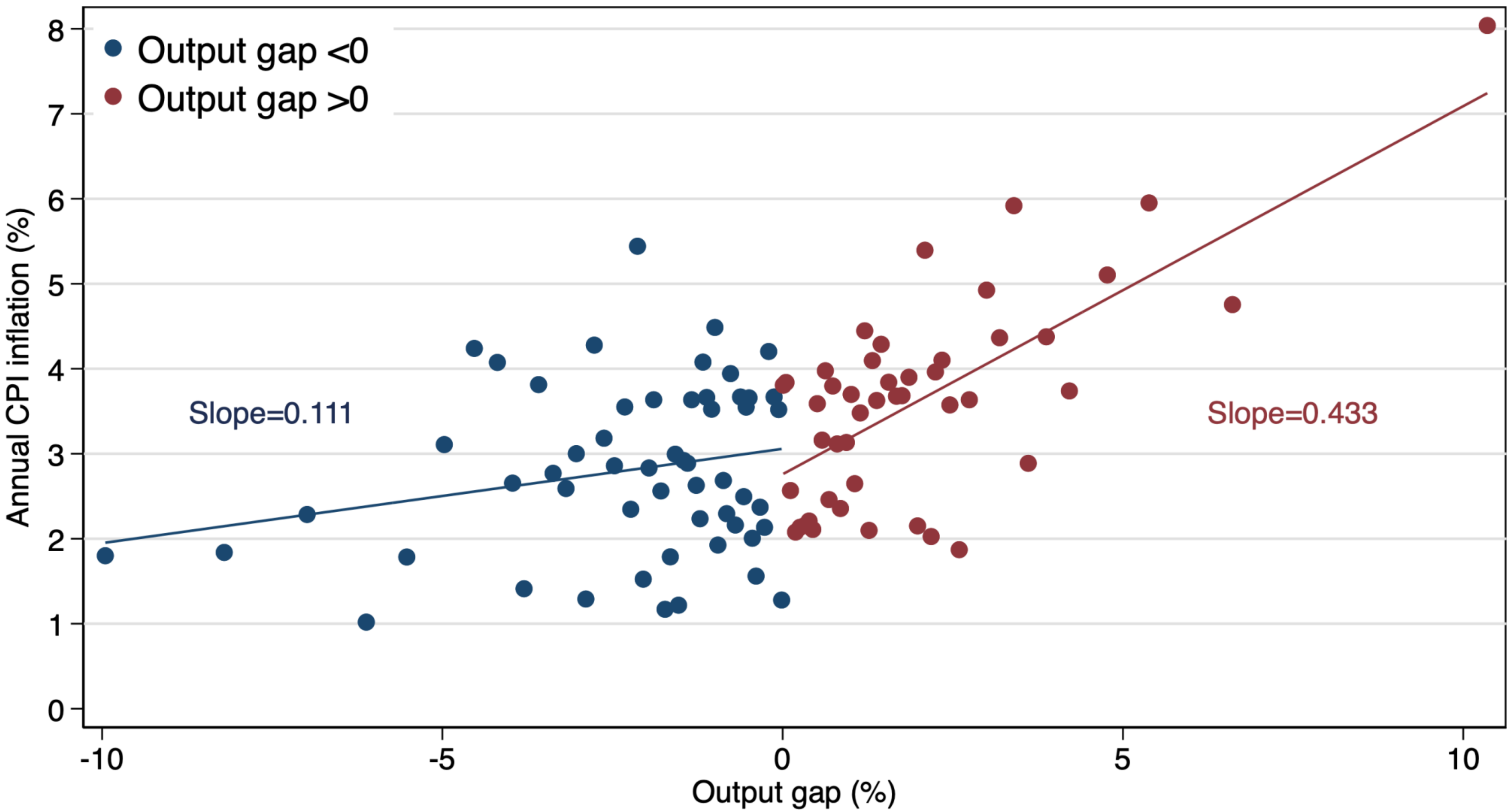
Main Figures

Figure 1: UK and US annual CPI inflation rates



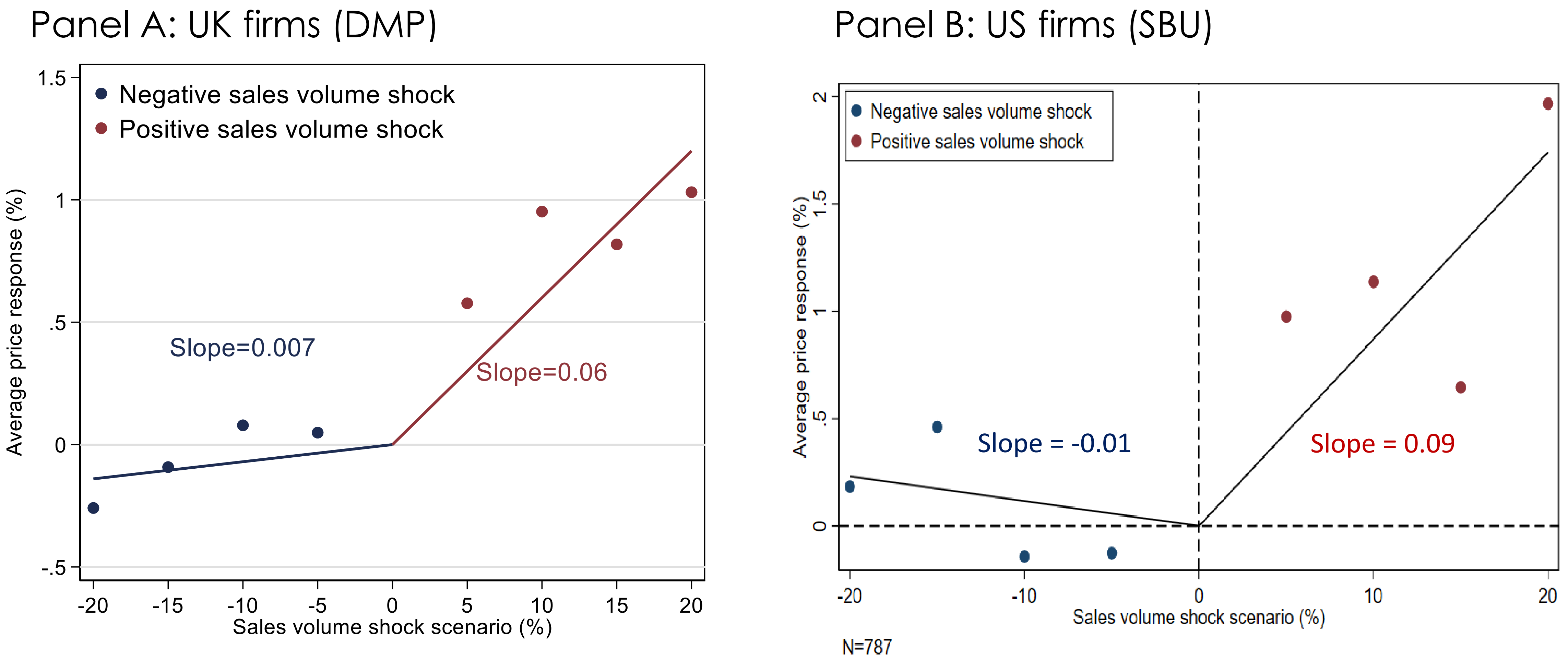
Notes: Data are three-month moving averages. Sources: UK Office for National Statistics and US Bureau of Labor Statistics.

Figure 2: Macro evidence on inflation and output gap



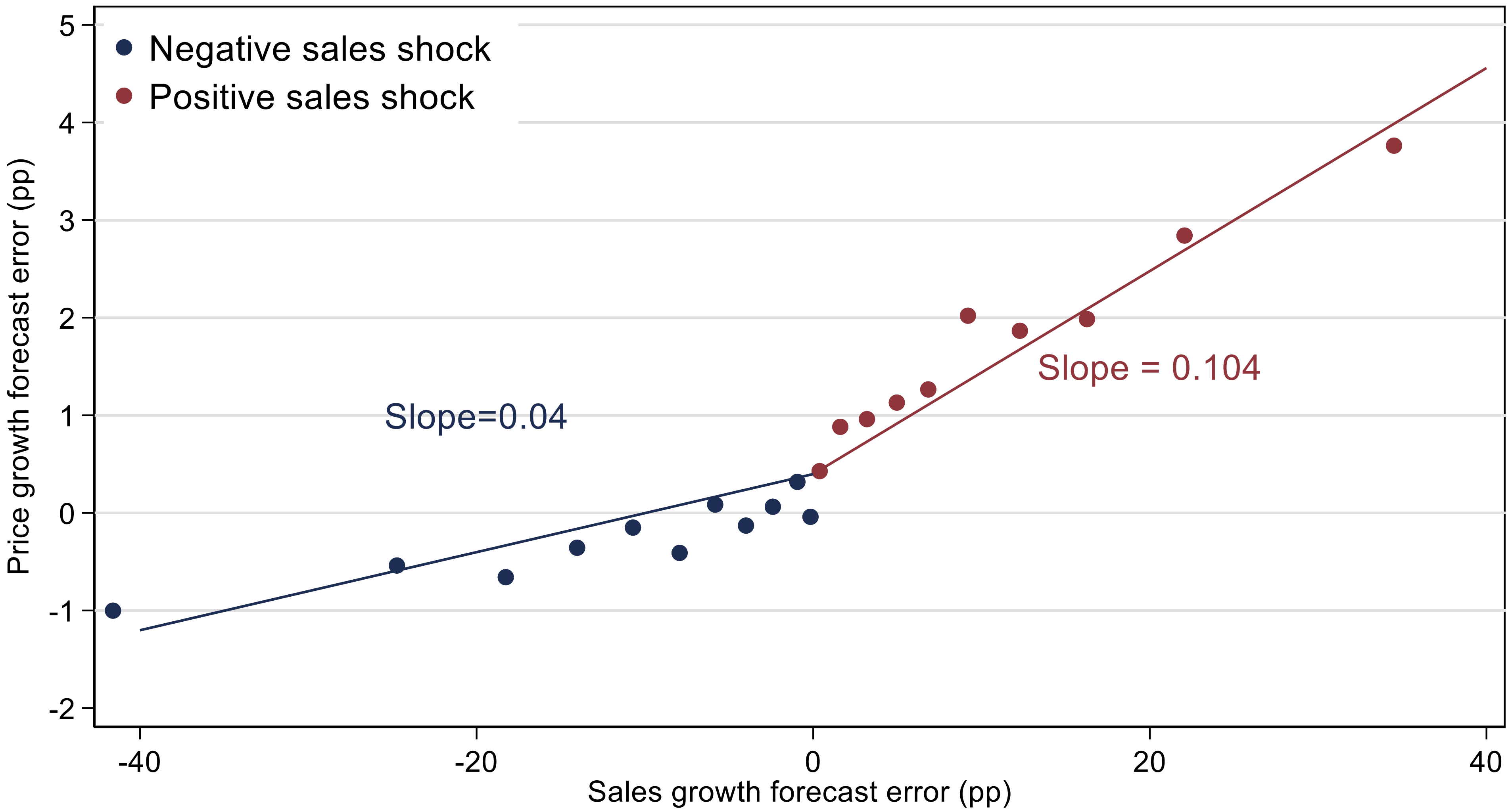
Notes: This figure is a binned scatterplot of annual CPI inflation rates on output gap estimates for 38 countries over the period 1990-2023. Data on annual inflation rates is taken from the World Bank cross-country database of inflation (Ha et al. 2023). Data on output gap estimates is obtained from the OECD.

Figure 3: Price response to hypothetical sales volume shocks



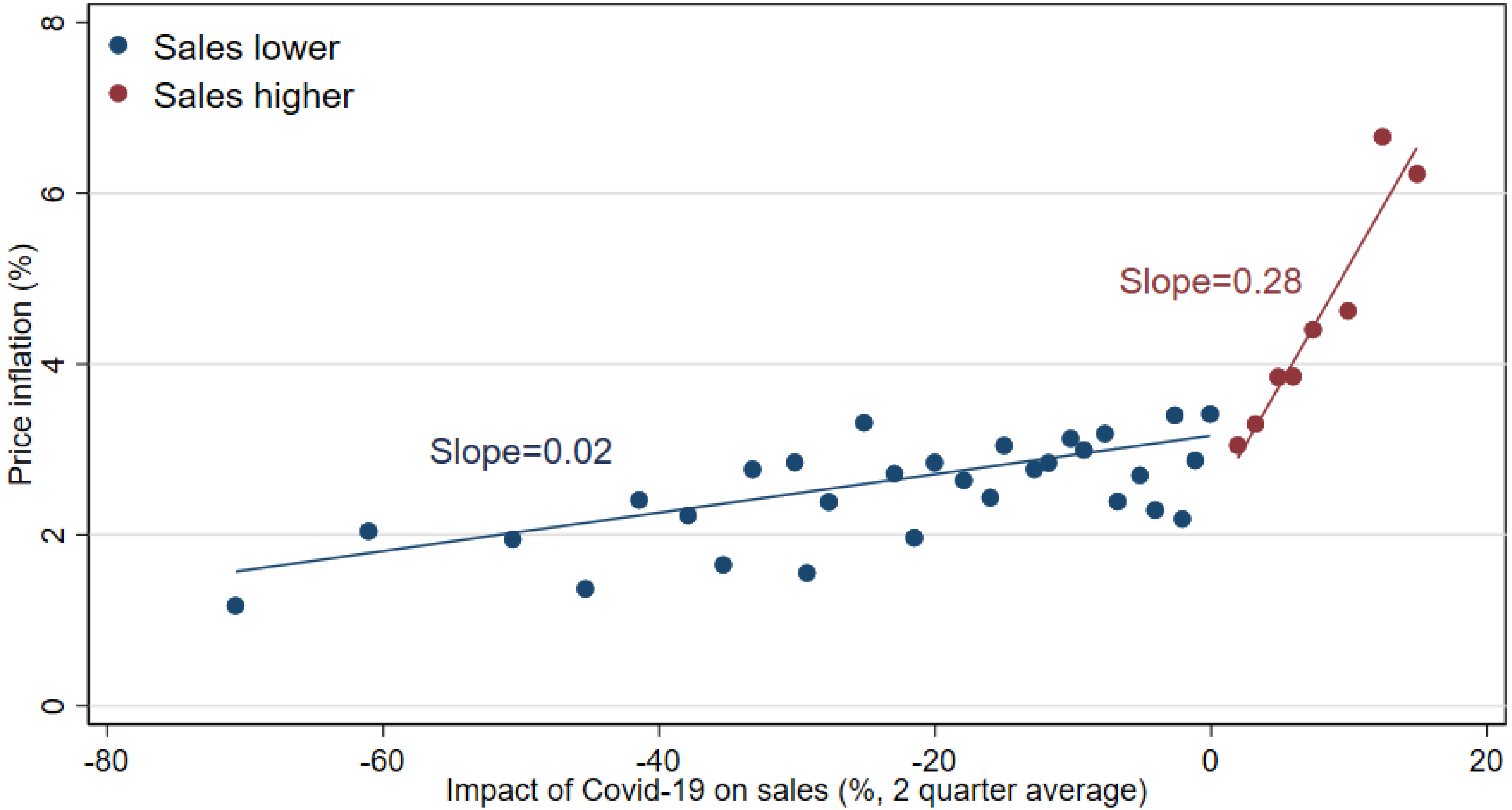
Notes: This figure reports responses to the question "Suppose that your business's sales volume over the next 12 months is X per cent higher/lower than you currently expect. How would that affect the average price you charge, relative to what you currently expect?" Firms are randomised into one of four scenarios for sales volume: ±5%, ±10%, ±15%, ±20%. Firms are presented with both the positive and negative values for a given scenario. Panel A is based on 6,394 observations from 2,486 UK firms in the Decision Maker Panel. Panel B is based on 787 US firms which responded to the June 2024 survey wave of the Survey of Business Uncertainty (see Meyer et al. 2024).

Figure 4: Relationship between sales and price forecast errors



Notes: This figure shows the relationship between nominal sales growth forecast errors and annual price growth forecast errors. Each dot represents 5% of the sample between January 2018 and October 2024. Sales forecast errors are trimmed at the 5th and 95th percentiles by quarter. Price forecast errors are winsorised at the 1st and 99th percentiles. The scatter plot is based on 20,027 observations for 4,142 UK firms in the Decision Maker Panel.

Figure 5: Realized inflation and impact of Covid-19 on sales



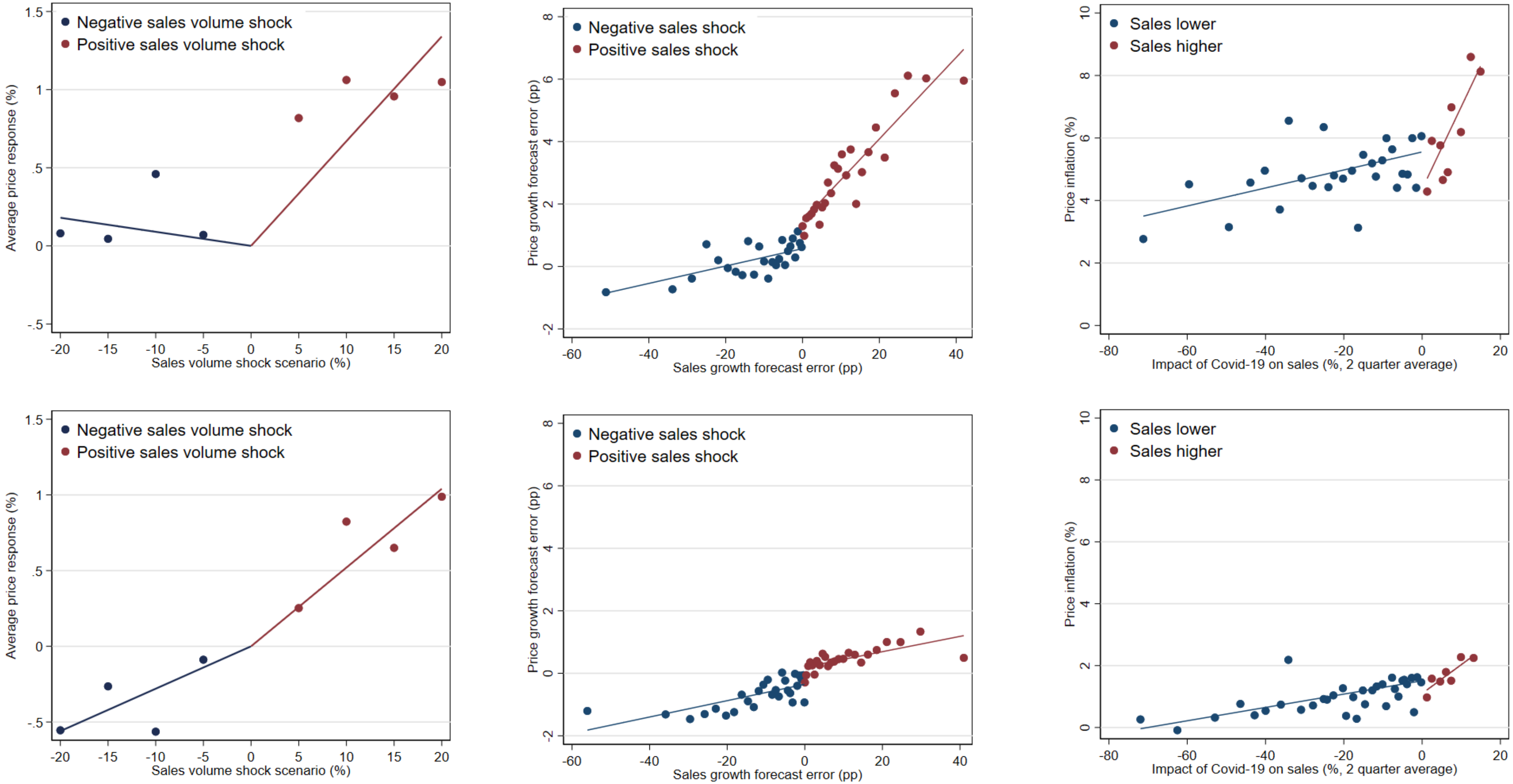
Notes: Each dot represents 2% of observations (during the pandemic, 2020 Q2 to 2022 Q2), grouped by impact of Covid-19 on sales. Zero responses are excluded. The scatterplot is based on 11,343 observations from 3,694 UK firms in the Decision Maker Panel.

Figure 6: Response to demand shocks: High vs. low inflation firms

Panel A: Hypothetical shocks | *Panel B: Forecast errors* | *Panel C: Covid demand shocks*

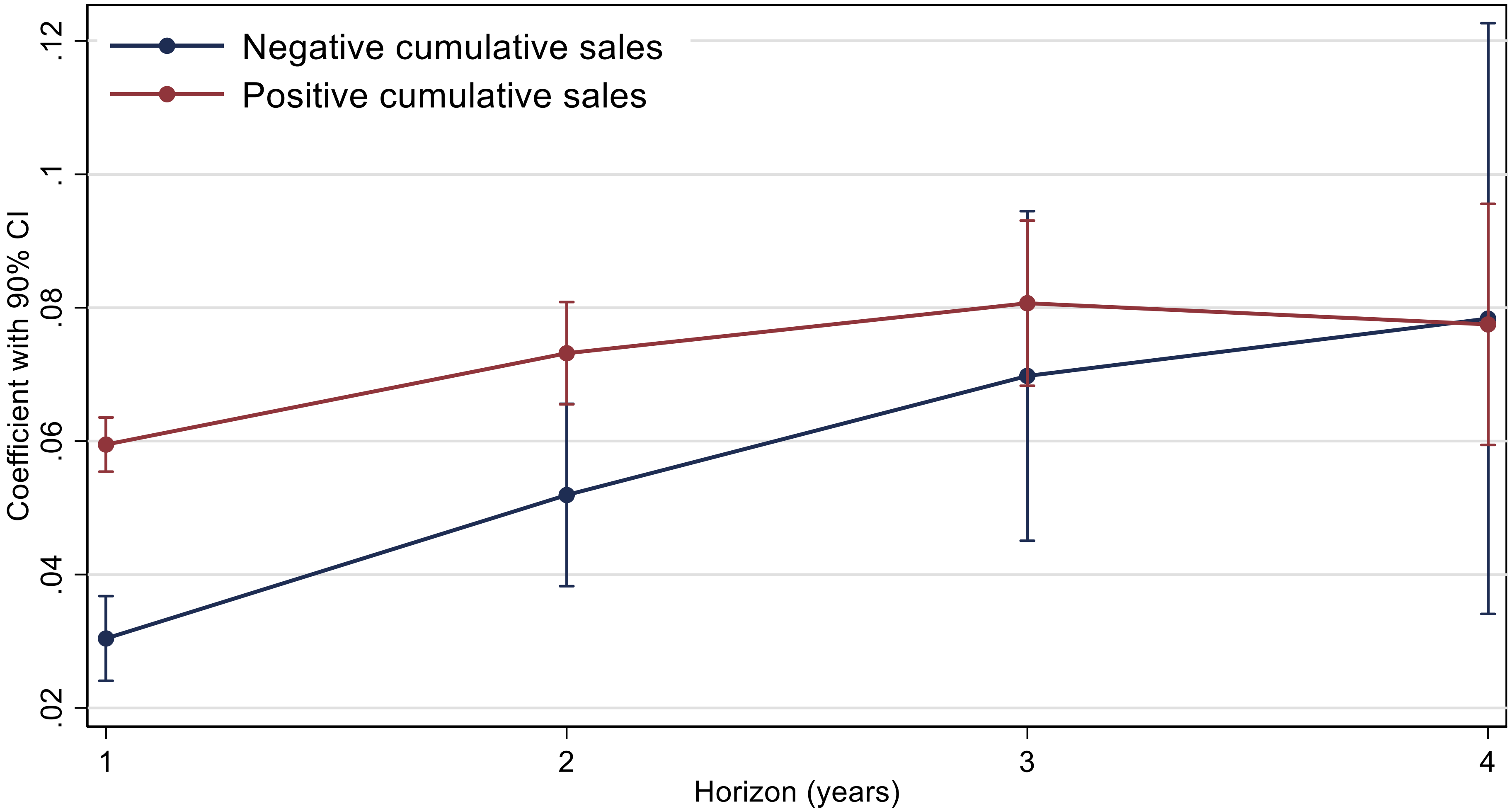
High Inflation Firms — **Average price growth: 7%**

Low Inflation Firms — **Average price growth: 1.5%**



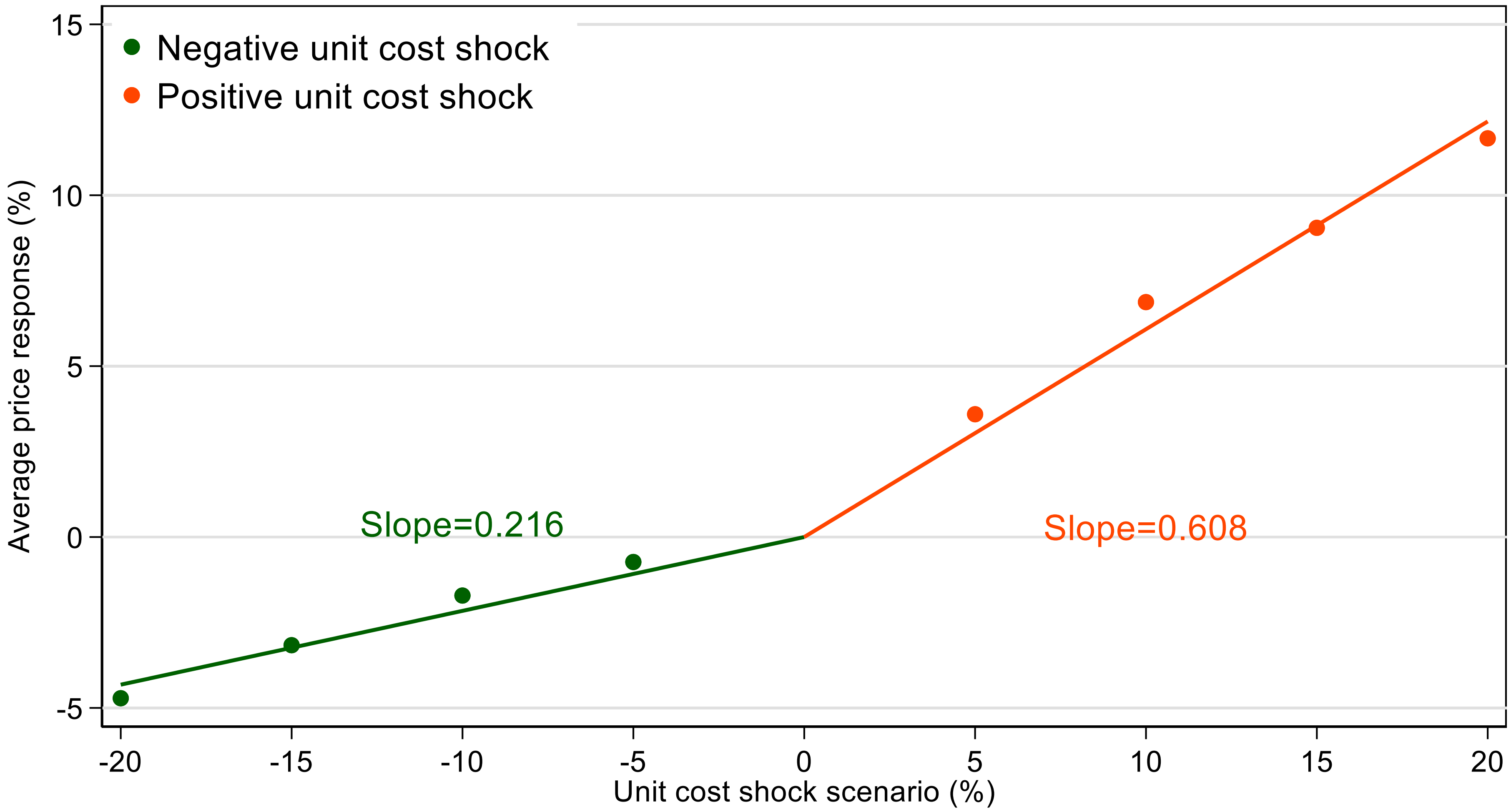
Notes: High-inflation firms are firms with average price growth across the full sample above 4% (sample average). Low-inflation firms are firms with average price growth across full sample below 4%. All figures are based on data from UK firms in the Decision Maker Panel.

Figure 7: Relationship between sales and price forecast errors: Longer-run responses



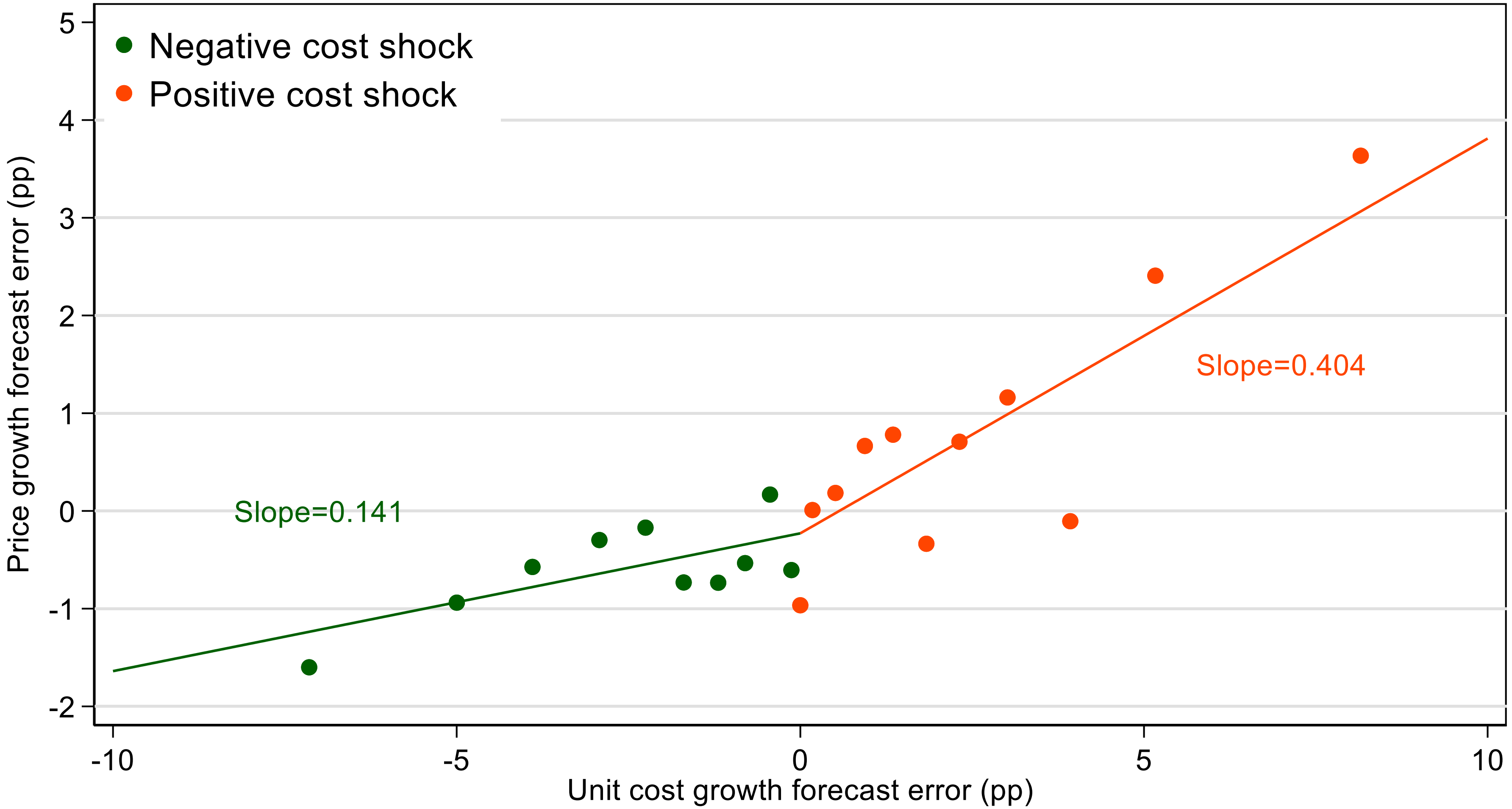
Notes: This figure presents the coefficients on regressions of cumulative own-price growth on cumulative nominal sales growth over horizons from one to four years. The coefficients on each horizon are based on separate regressions. Standard errors are clustered at the firm level and 90% confidence intervals are reported. This figure is based on data from UK firms in the Decision Maker Panel.

Figure 8: Price response to hypothetical unit cost shocks



Notes: This figure reports responses to the question ”Suppose that your business’s unit costs over the next 12 months are X per cent higher/lower than you currently expect. How would that affect the average price you charge, relative to what you currently expect?” Firms are randomised into one of four scenarios for unit costs: ±5%, ±10%, ±15%, ±20%. Firms are presented with both the positive and negative values for a given scenario. The scatter plot is based on 3,728 observations from 1,864 UK firms in the Decision Maker Panel. The results are unweighted.

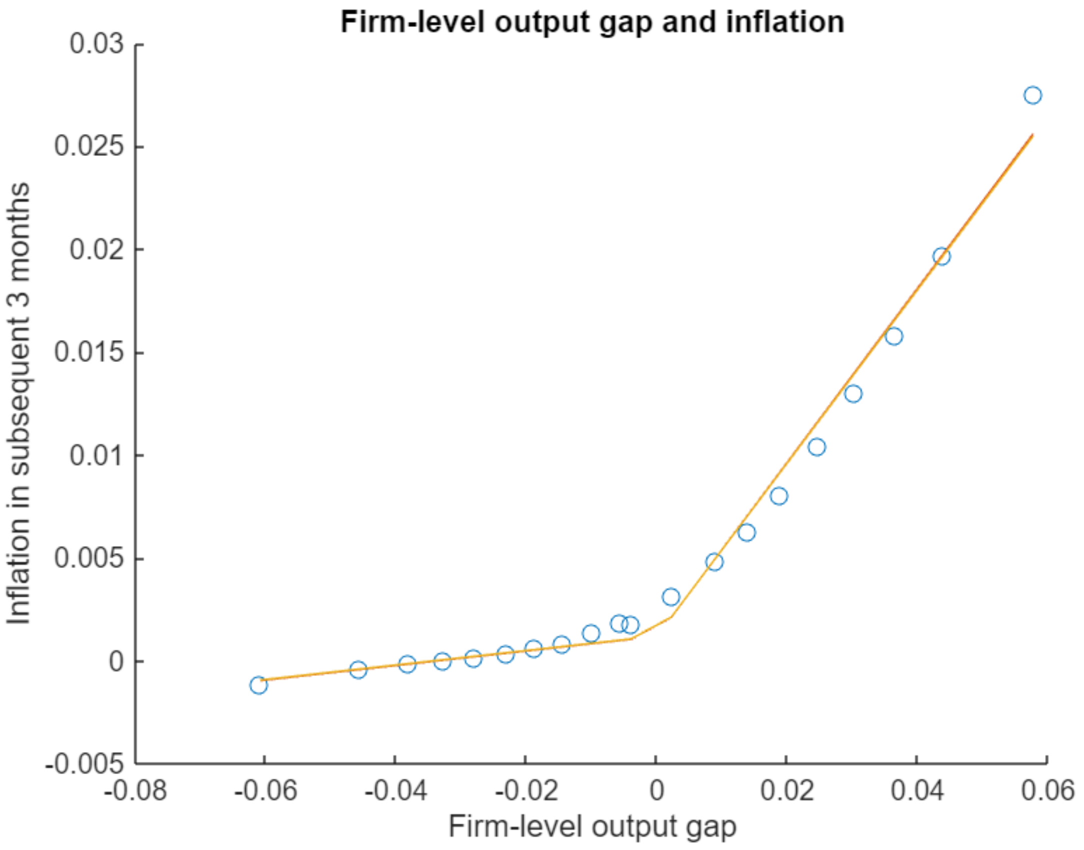
Figure 9: Relationship between unit cost and price forecast errors



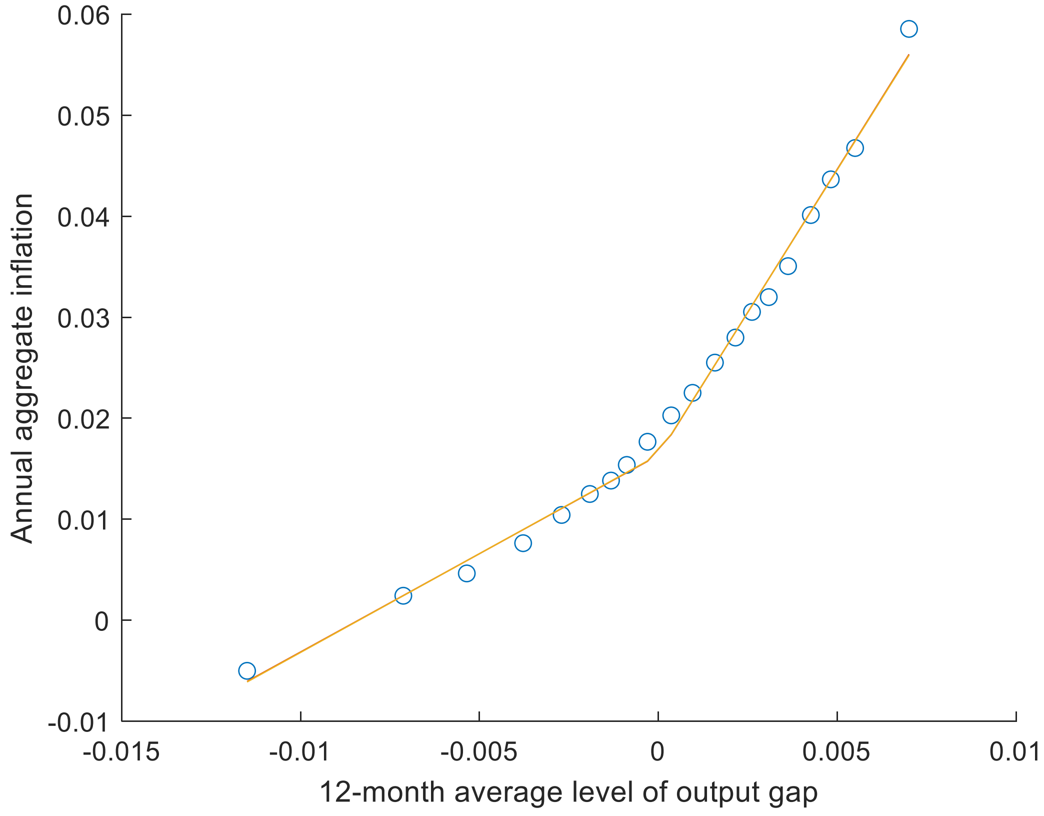
Notes: This figure shows the relationship between unit cost growth forecast errors and annual price growth forecast errors. Each dot represents 5% of the sample between 2018Q1 and 2024Q3 (with gaps). Unit cost growth forecast errors are trimmed at the 5th and 95th percentiles by quarter. Price forecast errors are winsorised at the 1st and 99th percentiles. The scatter plot is based on 1,621 observations for 1,155 UK firms in the Decision Maker Panel.

Figure 10: Results from menu cost model

Panel A: Firm simulated data



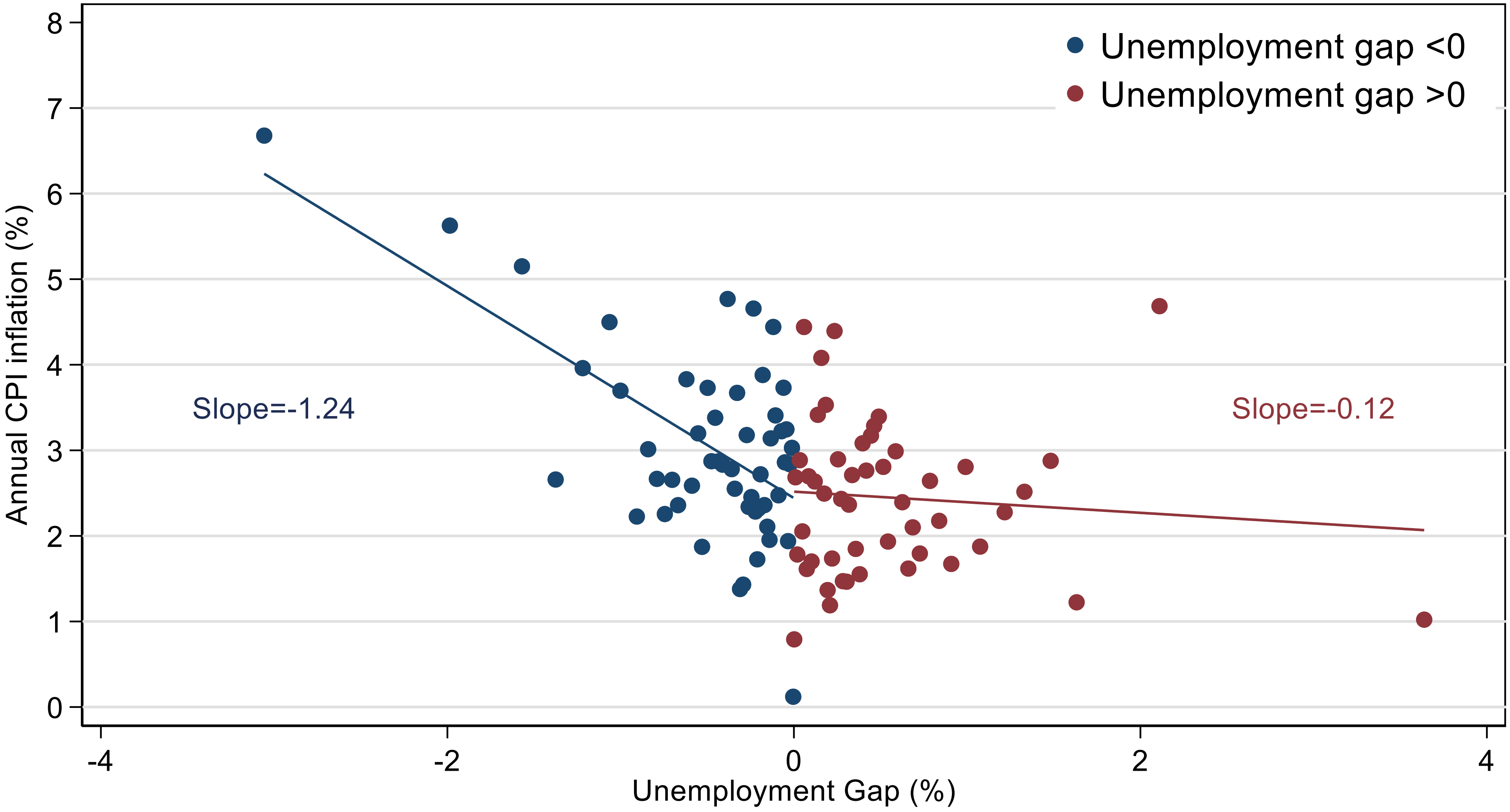
Panel B: Macro simulated data



Notes: This figure presents simulated data from the model at the firm level (Panel A) and aggregate level (Panel B), using the model outlined in Section 6.

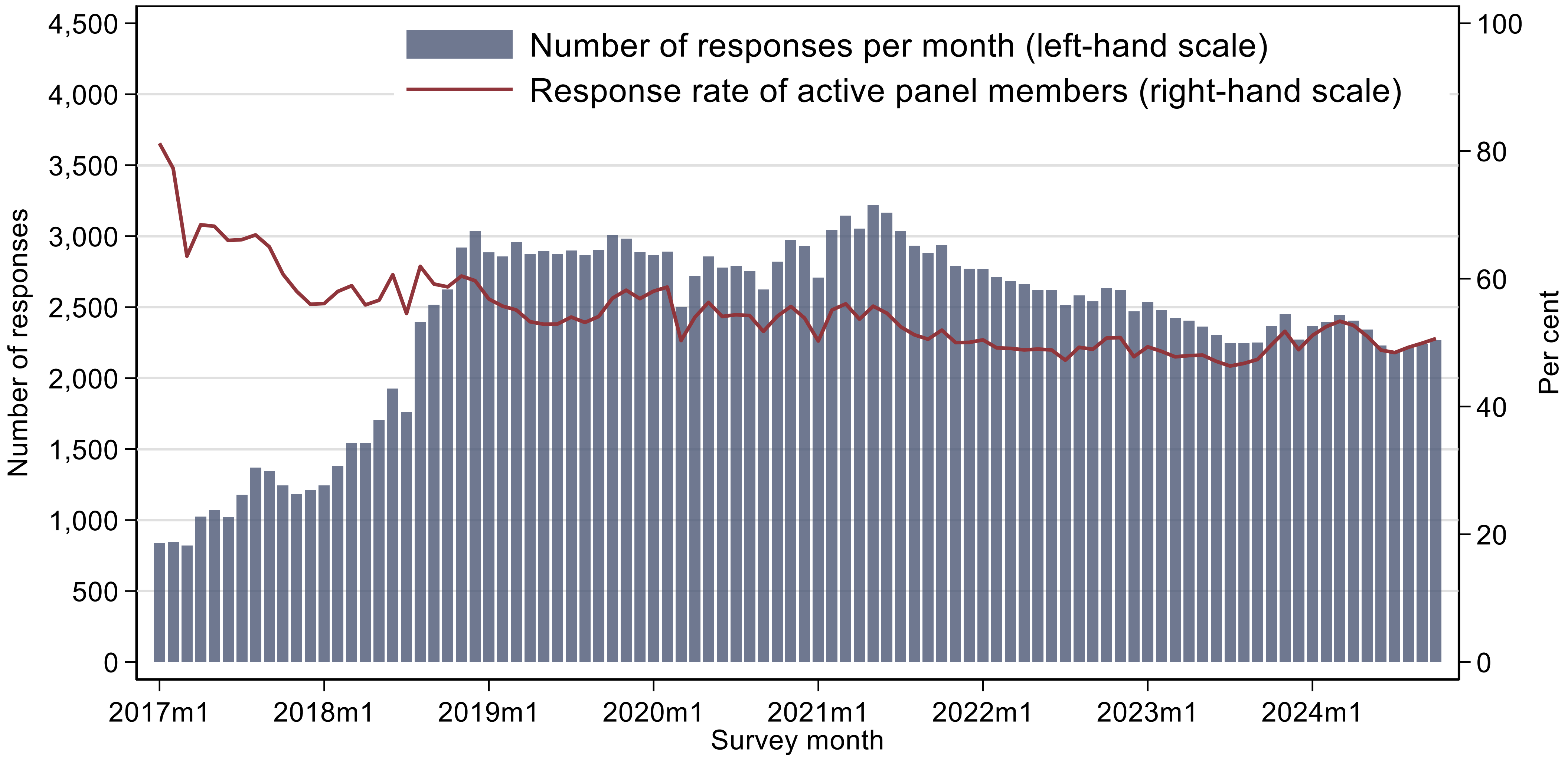
Appendix Figures

Figure A1: Macro evidence on inflation and unemployment gap



Notes: This figure presents a binned scatterplot of the relationship between aggregate inflation and the unemployment gap for the sample of countries in Figure 2. Each point represents roughly 1% of observations. Data on annual inflation rates are taken from the World Bank cross-country database of inflation (Ha et al. 2023). Data on unemployment are taken from the OECD. The unemployment gap is constructed using an HP filter for each country series. Country-years with inflation above 15% are dropped from the sample.

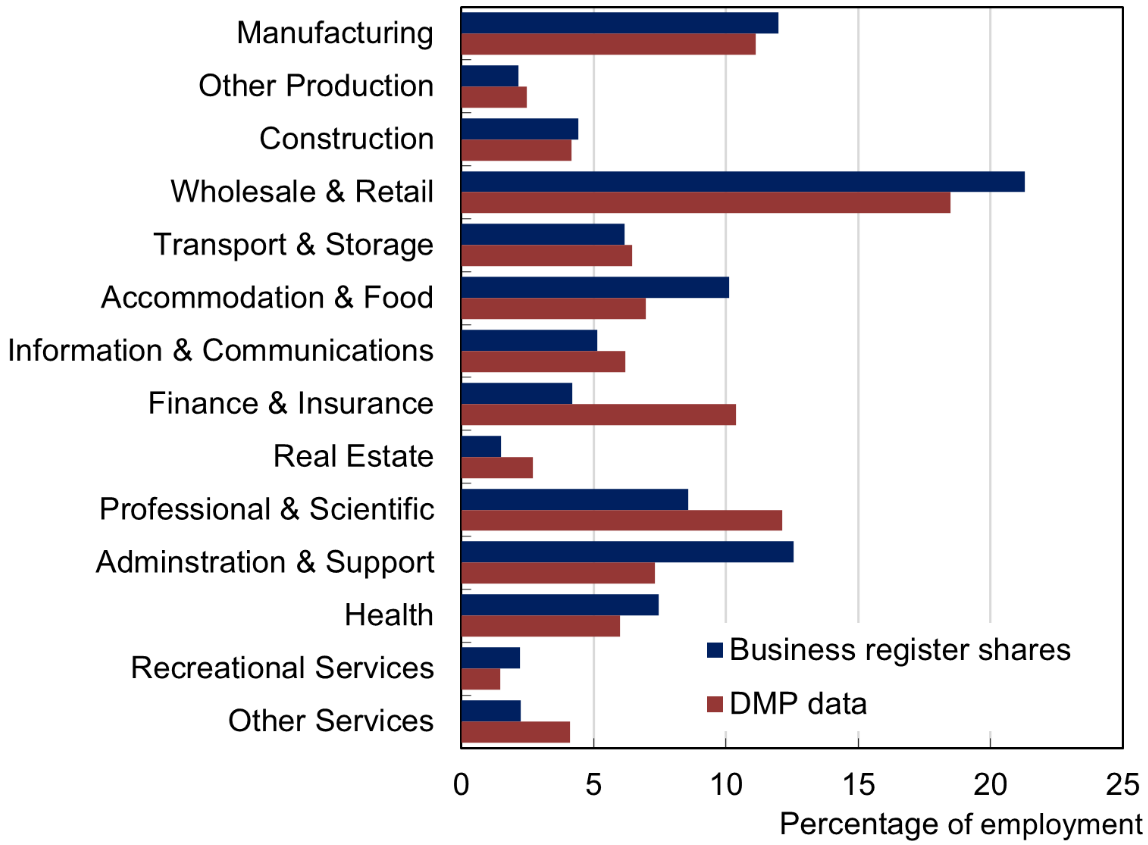
Figure A2: DMP Response rate



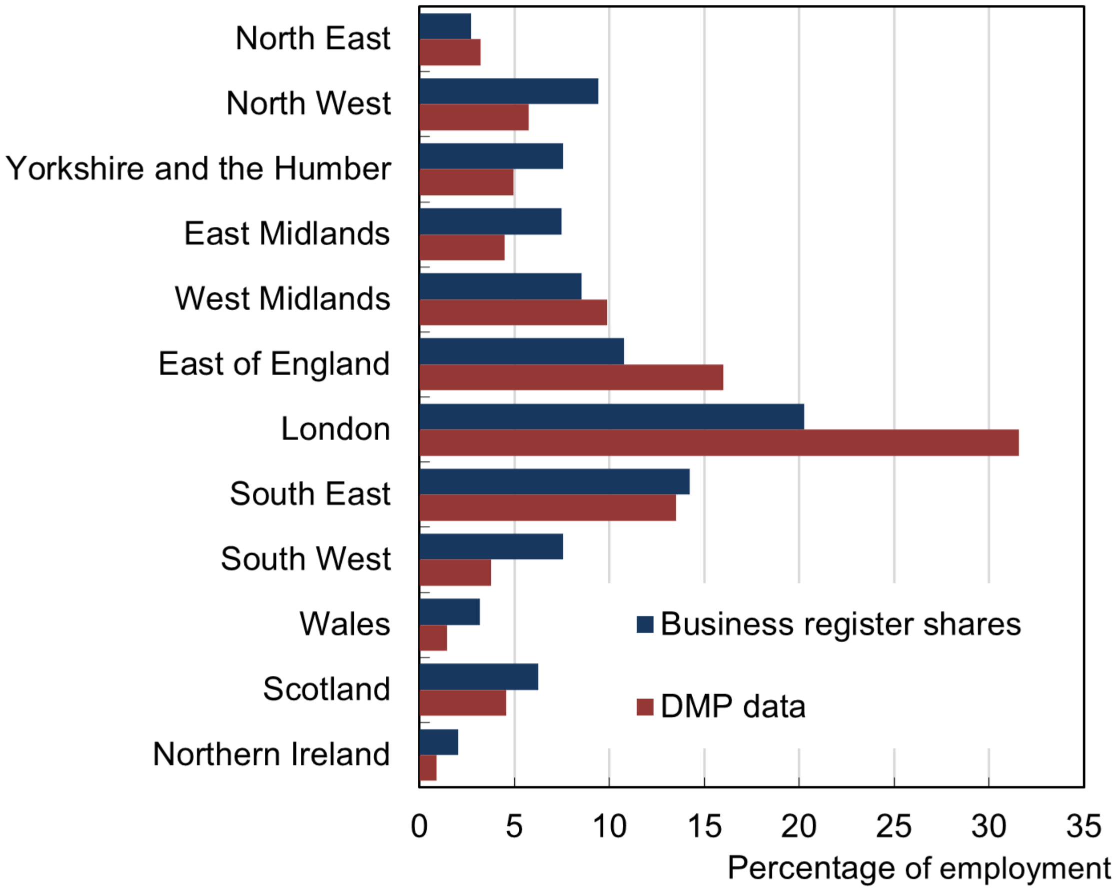
Notes: The response rate of active panel members in the Decision Maker Panel is calculated as the percentage of panel members who had completed at least one survey over the last twelve months who responded to the survey in a given month.

Figure A3: DMP vs. UK industrial and regional distribution

Panel A: By Industry

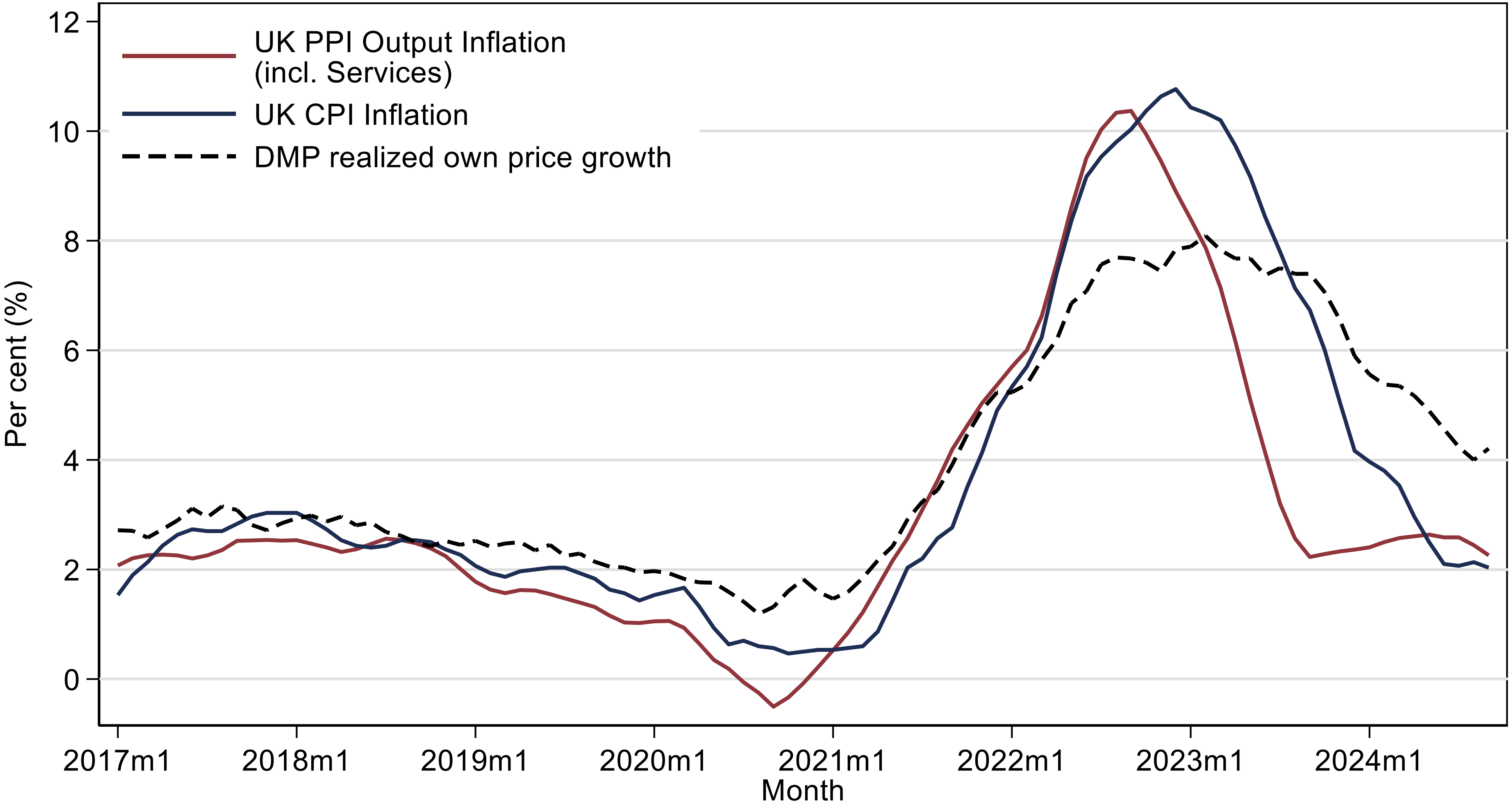


Panel B: By Region



Notes: Other production includes agriculture; forestry & fishing; mining & quarrying; electricity, gas & air conditioning supply; water supply; and sewerage, waste management & remediation activities. Data are averages from 2017 to 2023.

Figure A4: UK CPI inflation, UK PPI inflation, and DMP price growth



Notes: Data are three-month moving averages. Sources: DMP, UK Office for National Statistics. The PPI series combined data on output PPI inflation with quarterly data on Services PPI, with weights 0.33 and 0.67 respectively.

Figure A5: Expected inflation questions

Panel A: Scenarios

Decision Maker Panel

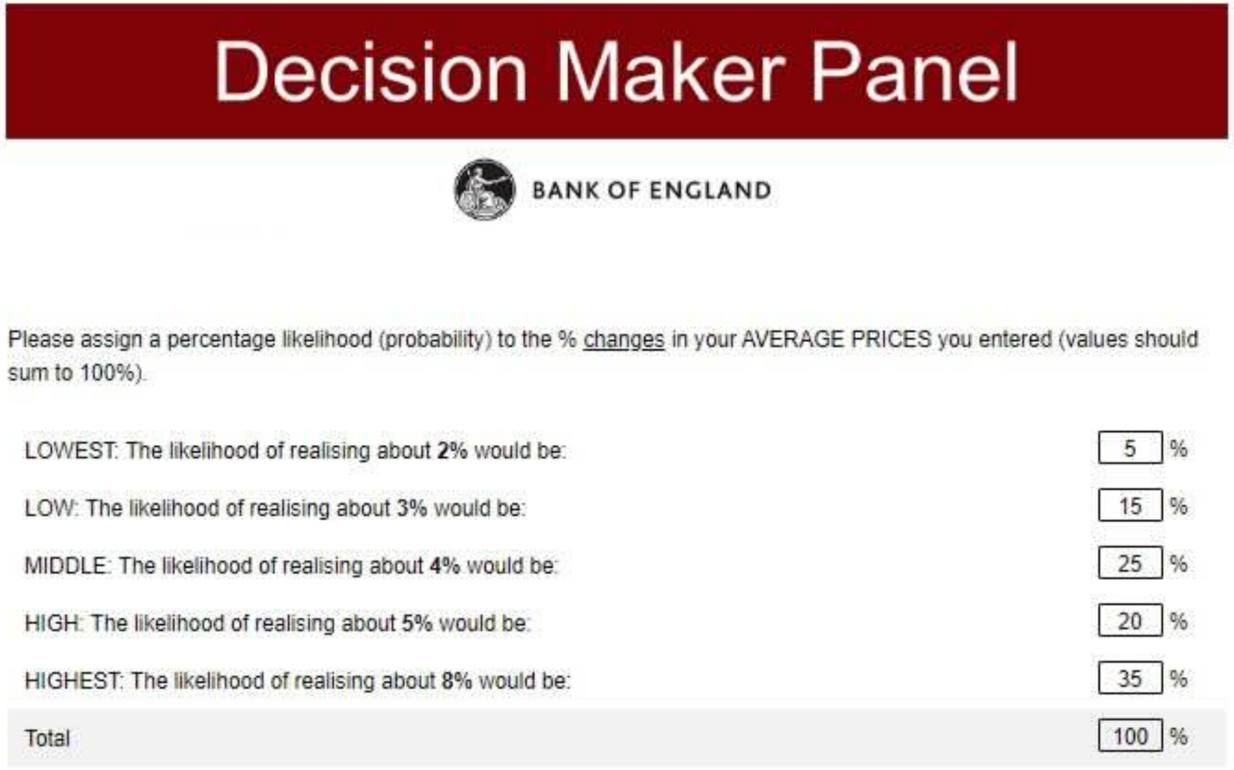
BANK OF ENGLAND

Looking ahead, from now to 12 months from now, what approximate % change in your AVERAGE PRICE would you expect in each of the following scenarios?

Note:
Price growth scenarios should be ordered from the lowest to the highest.

The LOWEST % change in my prices would be about:	2	%
A LOW % change in my prices would be about:	3	%
A MIDDLE % change in my prices would be about:	4	%
A HIGH % change in my prices would be about:	5	%
The HIGHEST % change in my prices would be about:	8	%

Panel B: Probabilities



Decision Maker Panel

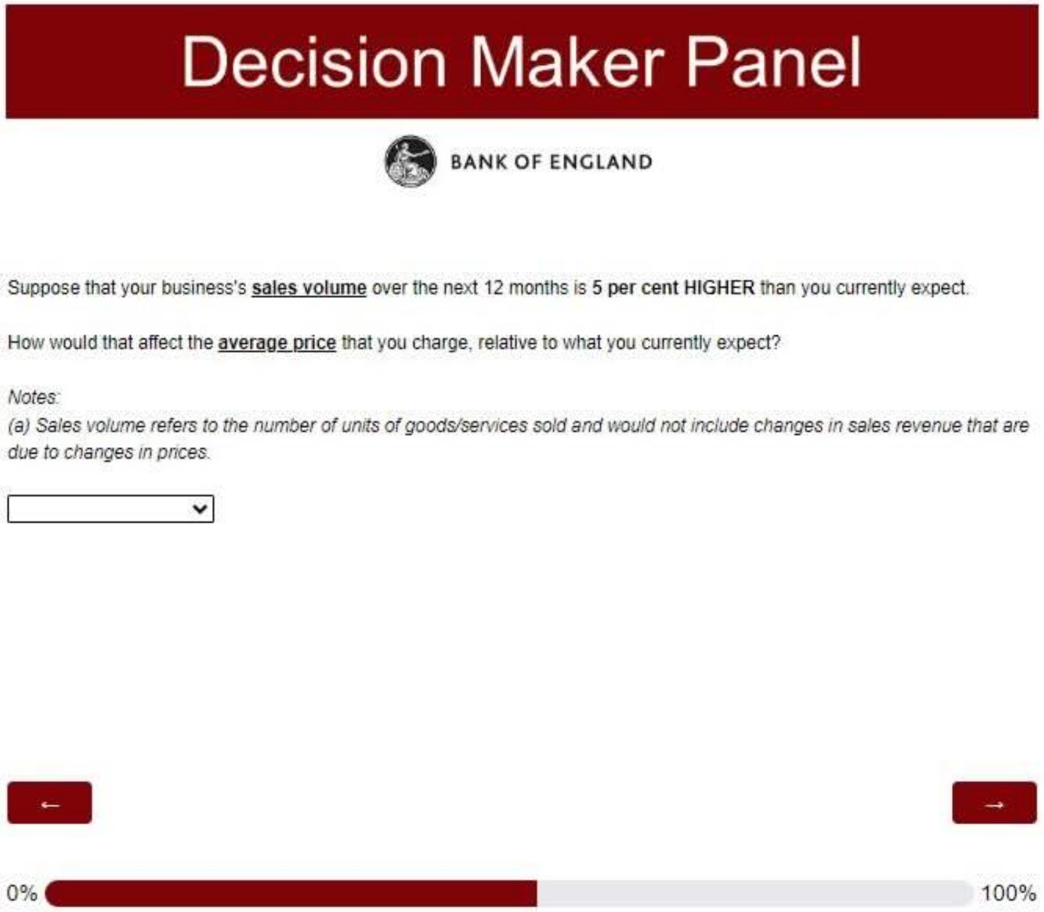
BANK OF ENGLAND

Please assign a percentage likelihood (probability) to the % changes in your AVERAGE PRICES you entered (values should sum to 100%).

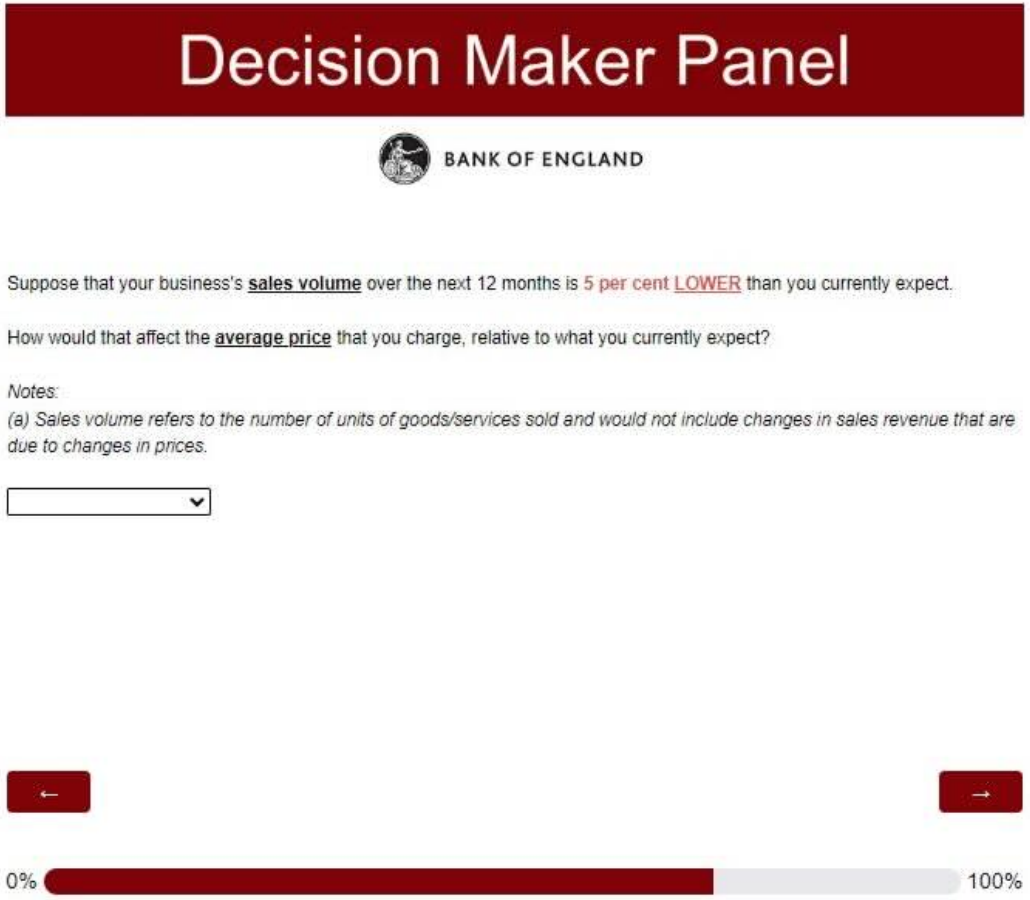
LOWEST: The likelihood of realising about **2%** would be:	5	%
LOW: The likelihood of realising about **3%** would be:	15	%
MIDDLE: The likelihood of realising about **4%** would be:	25	%
HIGH: The likelihood of realising about **5%** would be:	20	%
HIGHEST: The likelihood of realising about **8%** would be:	35	%
Total	100	%

Figure A6: Hypothetical sales volume shock questions

Panel A: Main scenario

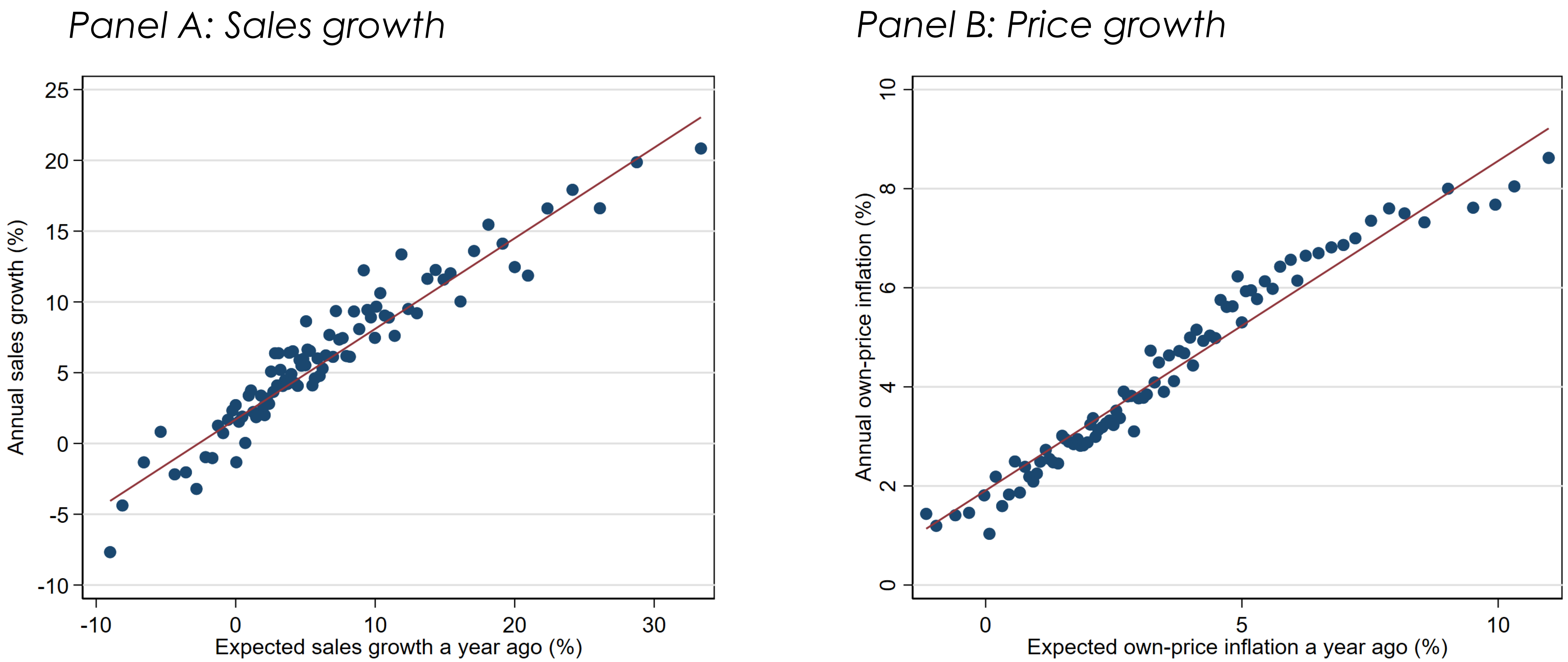


Panel B: Flipped scenario



Notes: Firms are randomised into one of four scenarios for sales volume: ±5%, ±10%, ±15%, ±20%. Firms are presented with both the positive and negative values for a given scenario. These questions were asked in December 2023 to January 2024, and in August 2024 to October 2024.

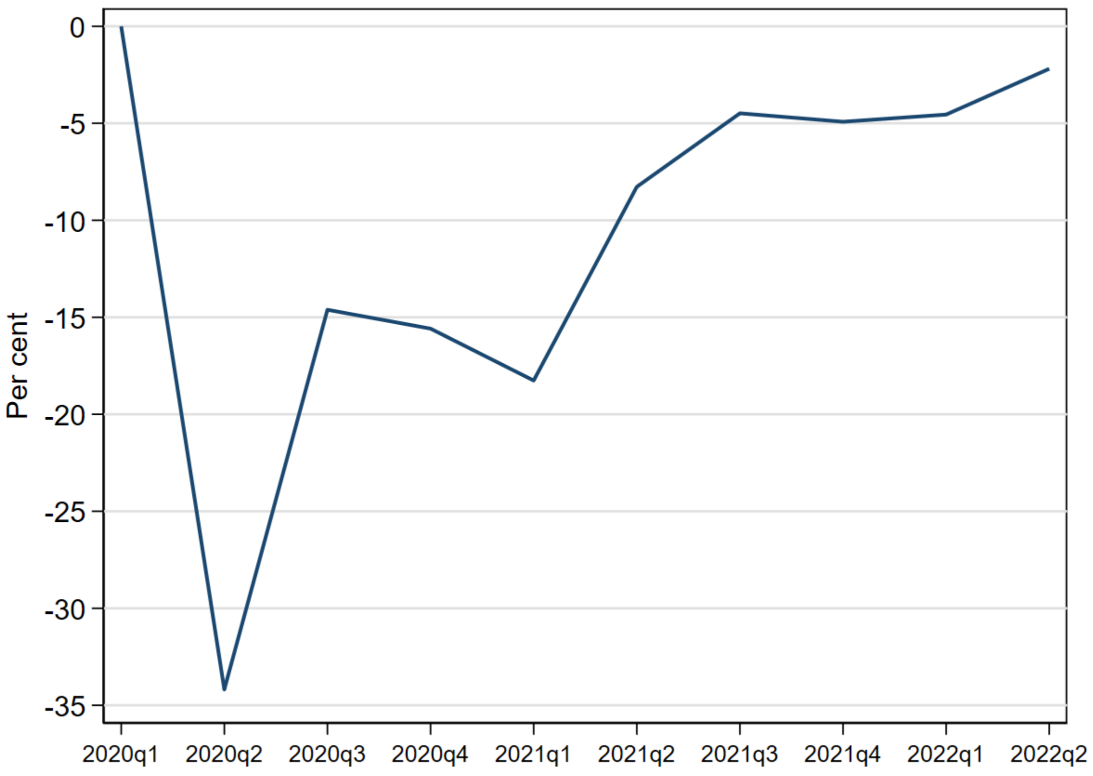
Figure A7: Comparison of firm year-ahead expectations with realizations



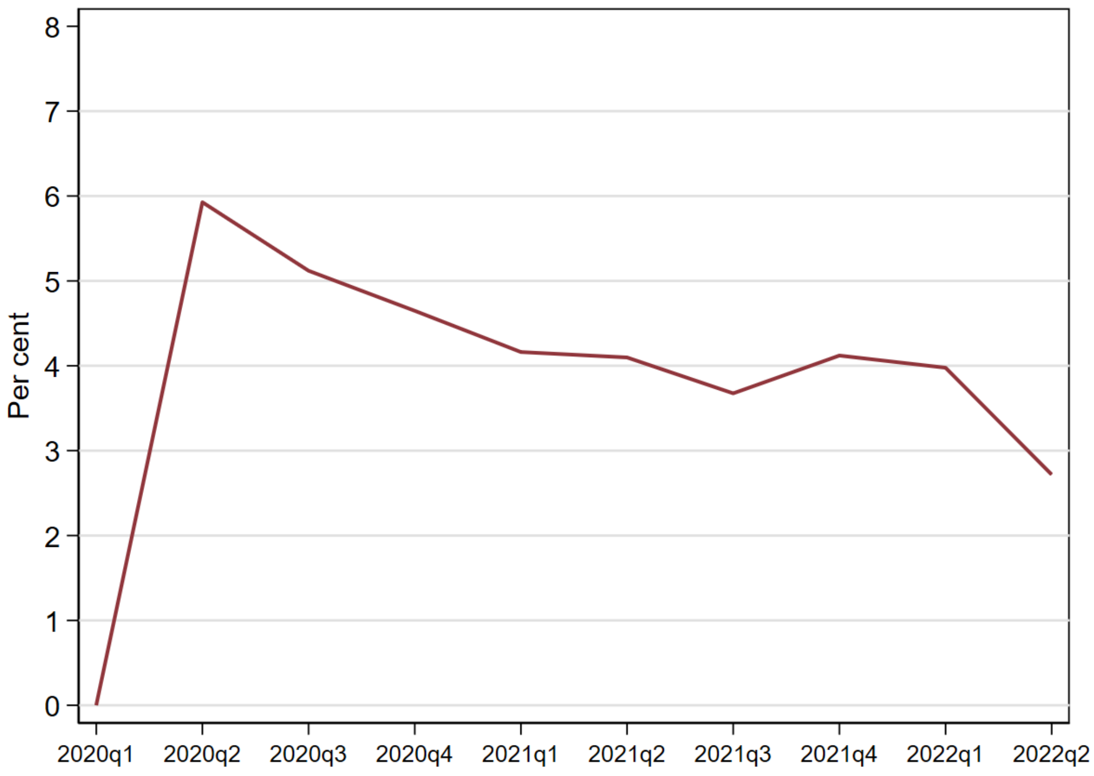
Notes: This figure presents binned scatter plots comparing year-ahead expectations for sales growth (Panel A) and price growth (Panel B) with realisations for the respective variables a year later. Each dot represents 1% of the sample. The figures are based on data from UK firms in the Decision Maker Panel over the period January 2019 to October 2024.

Figure A8: Impact of Covid-19 on sales and unit costs

Panel A: Sales



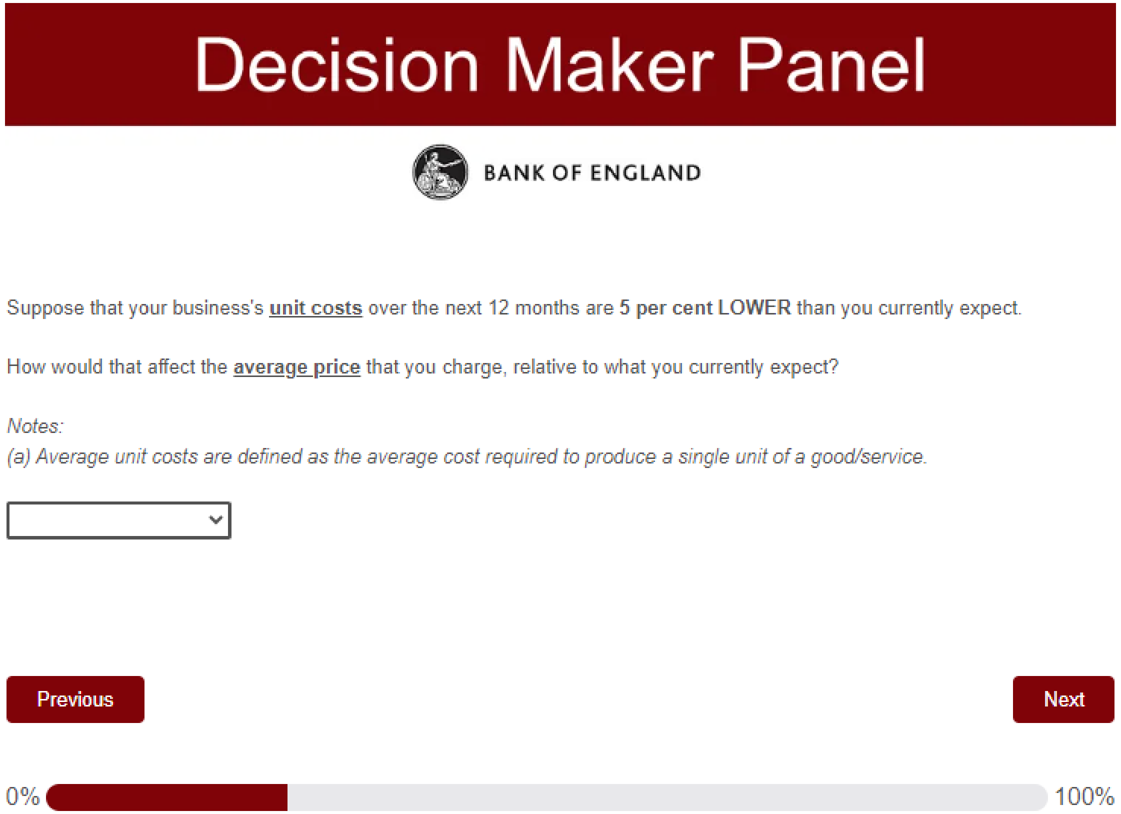
Panel B: Unit costs



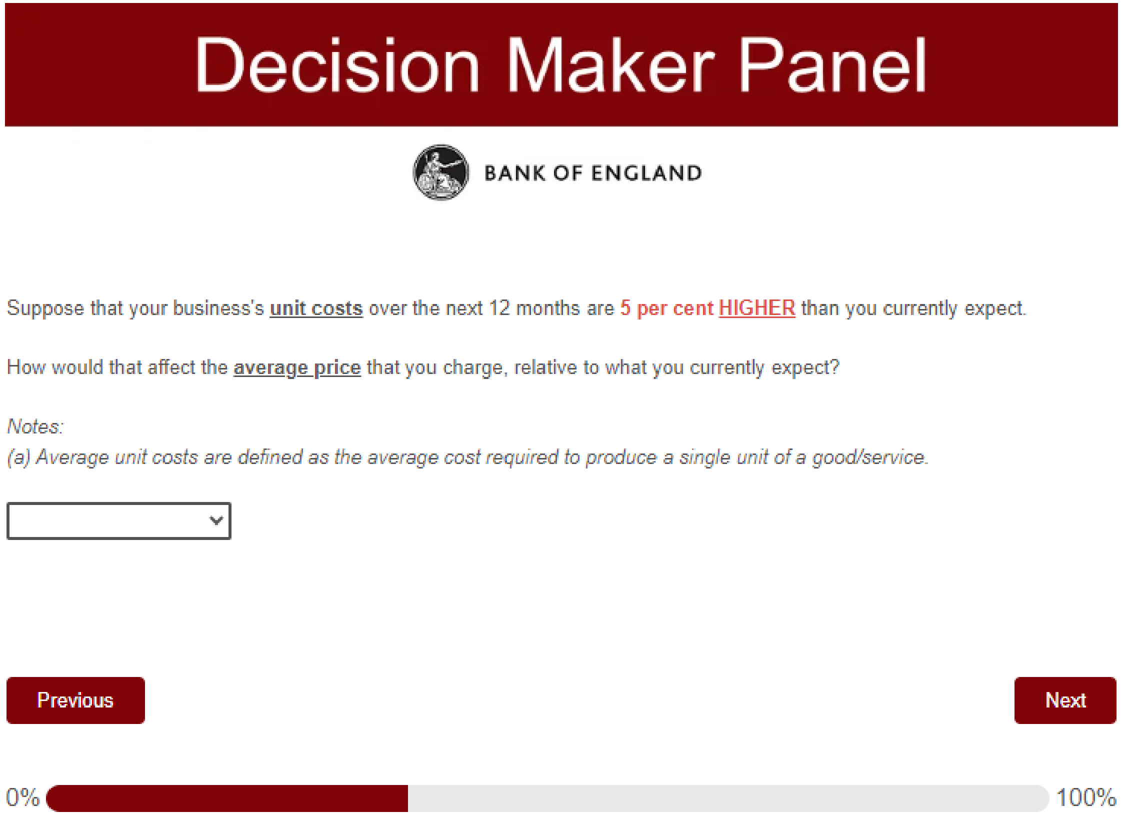
Notes: The results are based on the questions: 'Relative to what would otherwise have happened, what is your best estimate for the impact of the spread of Covid-19 on the sales of your business in each of the following periods?'; 'Relative to what would otherwise have happened, what is your best estimate for the impact of measures to contain coronavirus (social distancing, hand washing, masks and other measures) on the average unit costs of your business in each of the following periods?' The results are based on data from the DMP.

Figure A9: Hypothetical unit cost shock questions

Panel A: Main scenario

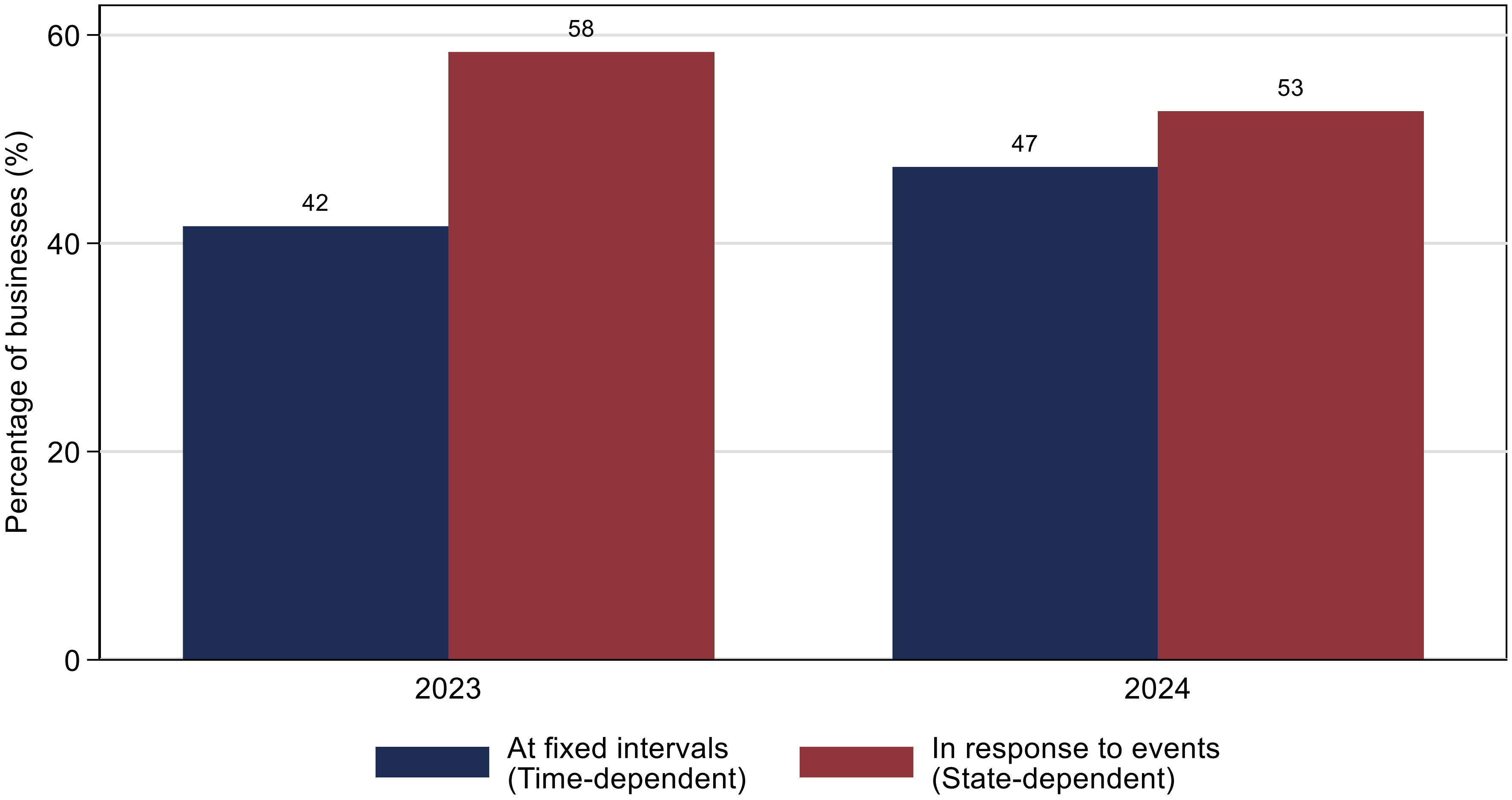


Panel B: Flipped scenario



Notes: Firms are randomised into one of four scenarios for unit costs: ±5%, ±10%, ±15%, ±20%. Firms are presented with both the positive and negative values for a given scenario. These questions were asked in August to October 2024.

Figure A10: How firms typically set prices



Notes: This figure is based on responses to the question: "Which of the following best describes how your business usually sets prices? 'Mostly change prices in response to specific events (eg changes in costs or demand)' or 'Mostly change prices at fixed intervals (eg once a year or once a quarter, etc)'". These results are based on data from UK firms in the Decision Maker Panel.

Main Tables

Table 1: Macro evidence on inflation and output gap

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dependent Variable:	Annual Headline CPI Inflation (%)						
Sample Period (annual data):	1990-2023					1990-2019	2020-2023
Output Gap_{it}	0.2231***	0.1538***	0.1205***	0.1277***			
	(0.0292)	(0.0415)	(0.0236)	(0.0217)			
Output Gap_{it}^2				0.0080***			
				(0.0024)			
Output Gap_{it} X OG > 0					0.1971***	0.1877***	0.4615**
					(0.0457)	(0.0444)	(0.1795)
Output Gap_{it} X OG < 0					0.0640*	0.0704*	-0.0834
					(0.0336)	(0.0383)	(0.0860)
Inflation_{it-1}			0.4845***	0.4812***	0.4809***	0.4952***	0.2573***
			(0.0370)	(0.0380)	(0.0385)	(0.0420)	(0.0494)
$E_t[\text{Inflation}_{it+5}]$			0.6678***	0.6817***	0.6879***	0.6842***	0.0219
			(0.0977)	(0.0996)	(0.1032)	(0.1124)	(0.8004)
Country fixed effects	No	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effects	No	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.061	0.599	0.800	0.802	0.801	0.770	0.896
Number of observations	1,146	1,146	1,115	1,115	1,115	969	146
Test coefficients equal (p-value)					0.046	0.095	0.017

Notes: Data on annual inflation rates is taken from the World Bank cross-country database of inflation (Ha et al. 2023). Data on output gap estimates is obtained from the OECD. Data on inflation expectations is taken from the IMF World Economic Outlook. Country-years with inflation above 15% are dropped from the sample. Standard errors are clustered at the country level and are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 2: Price response to hypothetical sales volume shocks

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent Variable:	Average Price Response (%)				Average price response (%)			
Sample:	UK Firms (DMP)				US Firms (SBU)			
Sample period:	Dec-2023, Jan-2024, Aug-2024 to Oct-2024				June 2024			
Sales volume shock	0.0338***	0.0338***			0.0365***	0.0377***		
	(0.0048)	(0.0048)			(0.0090)	(0.0089)		
Sales volume shock^2		0.0013***				0.0028***		
		(0.0002)				(0.0005)		
Sales volume shock X Shock > 0			0.0601***	0.0592***			0.0871***	0.1039***
			(0.0050)	(0.0095)			(0.0127)	(0.0128)
Sales volume shock X Shock < 0			0.0074	-0.0027			-0.0116	0.0478***
			(0.0072)	(0.0143)			(0.0123)	(0.0120)
R^2	0.013	0.019	0.021	0.018	0.0204	0.0555	0.0578	0.0943
Number of observations	6,394	6,394	6,394	6,392	1,574	1,574	1,574	1,574
Test coefficients equal (p-value)			0.000	0.000			0.0000	0.0014

Notes: This table reports results from the question ”Suppose that your business's sales volume over the next 12 months is X per cent higher/lower than you currently expect. How would that affect the average price you charge, relative to what you currently expect?” Firms are randomised into one of four scenarios for sales volume: ±5%, ±10%, ±15%, ±20%. Firms are presented with both the positive and negative values for a given scenario. The results in Columns 1-3 and 5-7 and are unweighted. The results in Columns 4 and 8 are weighted by industry and employment. US data are from Meyer et al. (2024). Standard errors are clustered at the firm level and are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 3: Relationship between sales growth and price growth forecast errors

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dependent variable:	Price growth forecast error (pp)					Price growth forecast error (pp)	
Sample period:	Nov-2017 to Oct-2024					Nov-2017 to Dec-2019	Jan-2020 to Oct-2024
Sales growth forecast error	0.0532***	0.0565***					
	(0.0038)	(0.0040)					
Sales growth forecast error^2		0.0005***					
		(0.0001)					
Sales growth forecast error X Error≥0			0.1036***	0.0747***	0.0722***	0.0517***	0.0757***
			(0.0069)	(0.0068)	(0.0069)	(0.0126)	(0.0073)
Sales growth forecast error X Error<0			0.0398***	0.0351***	0.0334***	0.0240*	0.0386***
			(0.0045)	(0.0055)	(0.0054)	(0.0127)	(0.0061)
Expected year-ahead own-price growth					0.1978***		
					(0.0358)		
Firm fixed effects	Yes	Yes	No	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	No	Yes	Yes	Yes	Yes
R2	0.365	0.367	0.046	0.366	0.384	0.453	0.387
Number of observations	18,831	18,831	20,027	18,831	18,274	3,340	14,843
Test coefficients equal (p-value)			0.000	0.000	0.000	0.174	0.000

Notes: This table shows the relationship between nominal sales growth forecast errors and annual price growth forecast errors. Sales forecast errors are trimmed at the 5th and 95th percentiles by quarter. Price forecast errors are winsorised at the 1st and 99th percentiles. The constant of the regressions are also estimated but not reported. All columns are based on data from UK firms in the Decision Maker Panel. Standard errors are clustered at the firm level and are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 4: Response of price growth to Covid demand shock

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dependent variable: Realized price inflation							
Sample period: 2017Q1 to 2022Q2 (quarterly data)							
Covid impact on $sales_{it}$#sales impact $positive_{it}$	0.2614***	0.2440***	0.1247***	0.0832***		0.1038***	0.0900***
	(0.0322)	(0.0311)	(0.0256)	(0.0163)		(0.0251)	(0.0245)
Covid impact on $sales_{it}$#sales impact $negative_{it}$	0.0131***	0.0055	0.0165***	0.0153***		0.0186***	0.0172***
	(0.0026)	(0.0035)	(0.0034)	(0.0034)		(0.0034)	(0.0034)
Dummy for Covid impact on sales $positive_{it}$	-0.2439	-0.7020***	-0.4119**			-0.3979**	-0.3966**
	(0.2172)	(0.2123)	(0.1776)			(0.1723)	(0.1678)
Covid impact on $sales_{it}$					0.0382***		
					(0.0060)		
(Covid impact on $sales_{it})^2$					0.0004***		
					(0.0001)		
Realized price inflation a year ago_{it} (firm level)							0.0818***
							(0.0157)
Expected price inflation a year $ahead_{it}$ (firm level)							0.3132***
							(0.0166)
Supply-side controls	No	No	No	No	No	Yes	Yes
Firm fixed effects	No	No	Yes	Yes	Yes	Yes	Yes
Time fixed effects	No	Yes	Yes	Yes	Yes	Yes	Yes
R2	0.019	0.138	0.546	0.546	0.546	0.560	0.582
Number of observations	34,076	34,076	34,076	34,076	34,076	34,076	34,076
Test coefficients equal (p-value)	0.000	0.000	0.000	0.000		0.001	0.004

Notes: Standard errors are clustered at the firm level and are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Impact of Covid on sales is an average of the current and previous quarter. Data is not available for all variables for all firms. Where data are missing for a particular variable, a dummy variable is included to account for that (results not reported), except for the impact of Covid on sales where all observations included in the regressions have data. All columns are based on data from UK firms in the Decision Maker Panel. Supply-side controls used in Columns 6 and 7 include: the impact of Covid on unit costs; share of non-labour inputs disrupted; a measure of recruitment difficulties; firm import intensity; the impact of Brexit on unit costs; energy costs in production. See Table A2 for the full specification.

Table 5: Price growth and demand shocks: High vs. low inflation

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable:	Average Price Response (%)		Price growth forecast error (pp)		Price growth (%)	
Firm Inflation:	High	Low	High	Low	High	Low
Sales volume shock X Shock>0	0.0667***	0.0516***				
	(0.0068)	(0.0075)				
Sales volume shock X Shock<0	-0.0094	0.0278**				
	(0.0096)	(0.0113)				
Sales growth forecast error X Error ≥0			0.1060***	0.0333***		
			(0.0108)	(0.0068)		
Sales growth forecast error X Error <0			0.0453***	0.0263***		
			(0.0100)	(0.0055)		
Covid impact on sales X sales impact ≥0					0.1420***	0.0606**
					(0.0354)	(0.0289)
Covid impact on sales X sales impact <0					0.0142**	0.0168***
					(0.0061)	(0.0036)
Firm fixed effects	No	No	Yes	Yes	Yes	Yes
Time fixed effects	No	No	Yes	Yes	Yes	Yes
R2	0.024	0.024	0.383	0.324	0.485	0.380
Number of observations	3,768	2,326	9,046	9,785	13,123	20,934
Test coefficients equal (p-value)	0.000	0.032	0.000	0.466	0.000	0.134
Difference coefficients positive/negative	0.076	0.024	0.061	0.007	0.128	0.044
Average firm price growth in sample (%)	7.312	2.598	6.778	1.953	5.251	1.433

Notes: High-inflation firms are firms with average price growth across the full sample above 4% (sample average). Low-inflation firms are firms with average price growth across full sample below 4%. All columns are based on data from UK firms in the Decision Maker Panel. Standard errors are clustered at the firm level and reported in parentheses, with *** p<0.01, ** p<0.05, * p<0.1.

Table 6: Relationship between sales and price forecast errors: Longer-run responses

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable:			Cumulative Price Growth (%)			
Horizon (Years):	1	2	3	4	4	4
Sales $\text{growth}_{t,t-1}$ X Sales growth ≥ 0	0.0595^{***}					
	(0.0025)					
Sales $\text{growth}_{t,t-1}$ X Sales growth < 0	0.0304^{***}					
	(0.0039)					
Sales $\text{growth}_{t+1,t-1}$ X Sales growth ≥ 0		0.0732^{***}				
		(0.0047)				
Sales $\text{growth}_{t+1,t-1}$ X Sales growth < 0		0.0519^{***}				
		(0.0083)				
Sales $\text{growth}_{t+2,t-1}$ X Sales growth ≥ 0			0.0807^{***}			
			(0.0075)			
Sales $\text{growth}_{t+2,t-1}$ X Sales growth < 0			0.0698^{***}			
			(0.0150)			
Sales $\text{growth}_{t+3,t-1}$ X Sales growth ≥ 0				0.0775^{***}	0.0476^{***}	0.0358^{***}
				(0.0110)	(0.0085)	(0.0072)
Sales $\text{growth}_{t+3,t-1}$ X Sales growth < 0				0.0784^{***}	0.0552^{***}	0.0211
				(0.0269)	(0.0181)	(0.0168)
Firm fixed effects	No	No	No	No	Yes	Yes
Time fixed effects	No	No	No	No	No	Yes
R2	0.035	0.047	0.055	0.050	0.740	0.798
Number of observations	50,971	21,357	10,349	5,207	4,816	4,816
Test coefficients equal (p-value)	0.000	0.047	0.565	0.979	0.728	0.455

Notes: This figure presents the coefficients on regressions of cumulative own-price growth on cumulative nominal sales growth over horizons from one to four years. All columns are based on data from UK firms in the Decision Maker Panel. Standard errors are clustered at the firm level and are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 7: Price response to hypothetical unit cost shocks

	(1)	(2)	(3)	(4)
Dependent Variable:	Average price response (%)			
Sample Period:	August-2024 to October-2024			
Unit cost shock	0.4122***	0.4122***		
	(0.0096)	(0.0096)		
Unit cost shock^2		0.0106***		
		(0.0004)		
Unit cost shock X Shock > 0			0.6080***	0.6179***
			(0.0132)	(0.0198)
Unit cost shock X Shock < 0			0.2165***	0.2470***
			(0.0105)	(0.0168)
R^2	0.416	0.497	0.510	0.542
Number of observations	3,728	3,728	3,728	3,728
Test coefficients equal (p-value)			0.000	0.000

Notes: This table reports results from the question ”Suppose that your business’s unit costs over the next 12 months are X per cent higher/lower than you currently expect. How would that affect the average price you charge, relative to what you currently expect?” Firms are randomised into one of four scenarios for unit costs: ±5%, ±10%, ±15%, ±20%. Firms are presented with both the positive and negative values for a given scenario. All columns are based on data from UK firms in the Decision Maker Panel. Standard errors are clustered at the firm level and are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 8: Relationship between unit cost growth and price growth forecast errors

	(1)	(2)	(3)	(4)	(5)
Dependent variable:	Price growth forecast error (pp)				
Sample period:	2018Q1-2024Q3 (with gaps)				
Unit cost growth forecast error	0.2862***	0.2788***			
	(0.0870)	(0.0875)			
Unit cost growth forecast error^2		0.0073			
		(0.0161)			
Unit cost growth forecast error X Error≥0			0.4041***	0.3788**	0.3910***
			(0.0739)	(0.1518)	(0.1466)
Unit cost growth forecast error X Error<0			0.1402*	0.1811	0.1271
			(0.0786)	(0.1608)	(0.1541)
Expected year-ahead own-price growth					0.5127***
					(0.1389)
Firm fixed effects	Yes	Yes	No	Yes	Yes
Time fixed effects	Yes	Yes	No	Yes	Yes
R2	0.514	0.514	0.042	0.515	0.552
Number of observations	902	902	1,621	902	889
Test coefficients equal (p-value)			0.034	0.446	0.289

Notes: This table shows the relationship between unit cost growth forecast errors and annual price growth forecast errors. Unit cost forecast errors are trimmed at the 5th and 95th percentiles by quarter. Price forecast errors are winsorised at the 1st and 99th percentiles. The constant of the regressions are also estimated but not reported. All columns are based on data from UK firms in the Decision Maker Panel. Standard errors are clustered at the firm level and are reported in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 9: Model parameters

Symbol	Parameter meaning	Baseline value	Source/rationale
β	Discount factor	0.96	Nakamura and Steinsson (2010)
θ	Elasticity of substitution between varieties	4	Nakamura and Steinsson (2010)
γ	Coefficient of relative risk aversion	1	Nakamura and Steinsson (2010)
ψ	Reciprocal of Frisch elasticity of labour supply	0	Nakamura and Steinsson (2010)
s_M	Share of intermediates in final output	0.7	Nakamura and Steinsson (2010)
λ	Returns to scale in production function	0.9	Khan and Thomas (2008)
K	Fixed cost of changing prices in labour units	0.003	To hit median frequency of price change to Nakamura and Steinsson (2010)
μ	Trend inflation rate	2.4% per year	Average inflation during 1992-2022
	Standard deviation of nominal demand shocks	0.011% (quarterly)	Std dev of HP-filtered nominal GDP during 1992-2022
	Persistence of demand shocks	0.9 per year	-
	Standard deviation of demand shocks	0.03	Analogue of Nakamura and Steinsson (2010)

Appendix Tables

Table A1: Sample of countries in macro dataset

Country	Number of observations	Country	Number of observations	Country	Number of observations
Australia	34	Greece	29	New Zealand	34
Austria	34	Hungary	25	Norway	34
Belgium	34	Iceland	31	Poland	27
Bulgaria	23	Ireland	29	Portugal	34
Canada	34	Israel	29	Romania	20
Chile	31	Italy	34	Slovak Republic	29
Croatia	14	Japan	34	Slovenia	28
Czech Republic	27	Korea, Rep.	34	Spain	34
Denmark	34	Latvia	25	Sweden	34
Estonia	26	Lithuania	21	Switzerland	34
Finland	34	Luxembourg	29	United Kingdom	34
France	34	Mexico	24	United States	34
Germany	33	Netherlands	34		

Table A2: Response of price growth to Covid demand shock

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dependent variable: Realized price inflation Sample period: 2017Q1 to 2022Q2 (quarterly data)							
Covid impact on sales$_{it}$#sales impact positive$_{it}$	0.2614***	0.2440***	0.1247***	0.0832***		0.1038***	0.0900***
	(0.0322)	(0.0311)	(0.0256)	(0.0163)		(0.0251)	(0.0245)
Covid impact on sales$_{it}$#sales impact negative$_{it}$	0.0131***	0.0055	0.0165***	0.0153***		0.0186***	0.0172***
	(0.0026)	(0.0035)	(0.0034)	(0.0034)		(0.0034)	(0.0034)
Dummy for Covid impact on sales positive$_{it}$	-0.2439	-0.7020***	-0.4119**			-0.3979**	-0.3966**
	(0.2172)	(0.2123)	(0.1776)			(0.1723)	(0.1678)
Covid impact on sales$_{it}$					0.0382***		
					(0.0060)		
(Covid impact on sales$_{it}$)^2					0.0004***		
					(0.0001)		
Covid impact on unit costs$_{i}$#2020Q2-2022Q2						0.0415**	0.0276*
						(0.0173)	(0.0158)
% of non-labour inputs disrupted$_{i}$#2021Q2-2022Q2						0.0402***	0.0305***
						(0.0062)	(0.0060)
Recruitment much harder than normal$_{i}$#2021Q2-2022Q2						0.6126***	0.5329**
						(0.2281)	(0.2174)
Import intensity$_{i}$#2021Q2-2022Q2						0.0082**	0.0068**
						(0.0035)	(0.0033)
Brexit impact on unit costs (2021 vs 2020)$_{i}$#2021Q2-2022Q2						0.1573***	0.1318***
						(0.0359)	(0.0336)
Percentage of costs that are petrol/coal (2 digit industry data)$_{i}$#2021Q2-2022Q2						0.1617***	0.1332***
						(0.0502)	(0.0478)
Percentage of costs that are electricity/gas (2 digit industry data)$_{i}$#2021Q2-2022Q2						0.5734***	0.4938***
						(0.1078)	(0.1050)
Realized price inflation a year ago$_{it}$ (firm level)							0.0818***
							(0.0157)
Expected price inflation a year ahead$_{it}$ (firm level)							0.3132***
							(0.0166)
Firm fixed effects	No	No	Yes	Yes	Yes	Yes	Yes
Time fixed effects	No	Yes	Yes	Yes	Yes	Yes	Yes
R2	0.019	0.138	0.546	0.546	0.546	0.560	0.582
Number of observations	34,076	34,076	34,076	34,076	34,076	34,076	34,076
Test coefficients equal (p-value)	0.000	0.000	0.000	0.000		0.001	0.004

Notes: Standard errors are clustered at the firm level and are reported in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$. All variables except the Covid effects on demand are time invariant for each firm and the coefficients on those variables are allowed to vary over time. Impact of Covid on sales is an average of the current and previous quarter. Impact of Covid on unit costs is an average from 2020 Q2 to 2022 Q2. The percentage of non-labour costs disrupted and whether a firm reports recruitment is much harder than normal (a dummy variable) are both averages between 2021 Q4 and 2022 Q2. Import intensity is the percentage of costs that were imports in 2016 H1. The impact of Brexit on unit costs is the percentage point change between 2021 and 2020. Industry energy cost data are for 2019 and are from the ONS Supply and Use tables. All other data used are from the DMP survey. Data is not available for all variables for all firms. Where data are missing for a particular variable, a dummy variable is included to account for that (results not reported), except for the impact of Covid on sales where all observations included in the regressions have data. All columns are based on data from UK firms in the Decision Maker Panel.

Table A3: Price growth and demand shocks: High vs. low inflation sectors

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable:	Average Price Response (%)		Price growth forecast error (pp)		Price growth (%)	
Inflation Sectors:	High	Low	High	Low	High	Low
Sales volume shock X Shock>0	0.0584***	0.0624***				
	(0.0066)	(0.0073)				
Sales volume shock X Shock<0	-0.0187**	0.0412***				
	(0.0093)	(0.0107)				
Sales growth forecast error X Error ≥0			0.0907***	0.0453***		
			(0.0103)	(0.0074)		
Sales growth forecast error X Error <0			0.0395***	0.0325***		
			(0.0082)	(0.0071)		
Covid impact on sales X sales impact ≥0					0.1605***	0.0564*
					(0.0351)	(0.0342)
Covid impact on sales X sales impact <0					0.0124**	0.0196***
					(0.0050)	(0.0047)
Firm fixed effects	No	No	Yes	Yes	Yes	Yes
Time fixed effects	No	No	Yes	Yes	Yes	Yes
R2	0.022	0.033	0.449	0.437	0.608	0.569
Number of observations	3,662	2,732	9,150	8,950	15,724	17,347
Test coefficients equal (p-value)	0.000	0.056	0.000	0.285	0.000	0.288
Difference coefficients positive/negative	0.077	0.021	0.051	0.013	0.148	0.037
Average firm price growth in sample (%)	6.537	4.801	5.436	3.081	3.721	2.152

Notes: High-inflation sectors are sectors for which the average SIC3 price growth (excluding firm i) in a given year exceeds the average price growth in the same year for all firms. All columns are based on data from UK firms in the Decision Maker Panel. Standard errors are clustered at the firm level and are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.